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A Conditional Approach to Projecting Farm Structure

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ABSTRACT

The traditional approach to projecting the distribution of farms by size uses a Markov model with stationary (constant) transition probabilities. While a useful tool for extrapolation of current trends, the stationary Markov approach cannot model the impacts on farm structure of varying economic and social causal forces. Data are now available for developing Markov models with nonstationary transition probabilities. A simple nonstationary Markov model of U.S. farm structure is described and estimated, and its performance in predicting actual changes in farm numbers and sizes through 1986 is assessed. Further issues in the development of conditional projections of farm structure are discussed.

Keywords: Farm structure, projections, Markov analysis, nonstationary transition probabilities.

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SUMMARY

This report describes an approach for developing conditional projections of the U.S. farm structure. By using the nonstationary variant of the Markov model commonly employed in U.S. farm structure research, alternative outcomes can be projected for the numbers and sizes of U.S. farms due to varying causal factors. The nonstationary Markov model, thus, provides a means for incorporating microlevel determinants of entry, exit, growth, and shrinkage of farms into projections of the aggregate characteristics of the farm sector.

A nonstationary Markov transition probability matrix represented by a set of multinomial logit functions was specified and estimated from nine regional observations of 1974-78 transition probabilities. The results are promising. Where t-tests are significant, statistical relationships between the observed transition probabilities and variables representing hypothesized causal factors carry the expected signs. More important, the estimated nonstationary Markov model yields projections that are closer to the actual 1982 and 1986 farm size distributions than those generated by a stationary Markov model derived from the same microdata.

At a minimum, these results illustrate the critical role played by model specification in influencing projections of farm structure. Using the same 1974-78 census data in both cases, a stationary Markov model generates a projected path of farm structural change that does not deviate greatly from the 1974-78 trend of relative stability. A nonstationary Markov model that makes fuller use of the information available in those data, however, generates a path of structural change that seems to come closer to what actually occurred after 1978.

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INTRODUCTION

What the U.S. farm sector will be like in the future is a question that has occupied considerable attention among economists, businesspeople, and policymakers. The problem comes posed in a variety of contexts, ranging from how particular policy or price regimes will engender changes in individual farm firms to whether or how these factors will transform the aggregate structure of the industry.1/

A well-developed body of theory and analytical methods already exists for assessing firm-level responses to changes in the economic environment (for examples, see [2] and references therein).2/ At the aggregate level, however, assessing the impacts of institutional, technological, and outside economic factors on the organization and performance of agriculture has proven much more complex.

The literature discussing the general qualitative impacts on farm structure of a range of causal factors is large. It is typified by studies conducted by U.S. Department of Agriculture (USDA) in the late 1970's [23] and by the Office of Technology Assessment (OTA) in the 1980's [15]. Both of these studies emphasized the significant and differing potential impacts on farm structure of alternative scenarios for policy and technology. Yet, the forecasts of farm numbers and sizes from each of these major research efforts failed to link either the quantitative firm-level or qualitative sectoral adjustments anticipated by researchers with projected quantitative changes in farm structure. Instead, structural projections have for the most part been linear extrapolations of historical trends [4, 14, 15].

Projections of farm structural change that are contingent on alternative economic environments are difficult to make for several reasons. The reasons fall into three main categories: adequacy of theory, data, and models.

1/The term "farm structure" can be defined in a variety of ways to refer to the number of farms, their sizes in terms of inputs or outputs, or their legal or financial structure. The term is used here in the limited form most commonly found in the agricultural economics literature, to denote the numbers of farms by their size in acres or gross value of sales.

2/Underscored numbers in brackets refer to items in the References section.

First, the theoretical basis on which to make predictions of aggregate changes in industrial structure is not well developed, particularly in the case of agriculture, where hundreds of thousands of integrated firm-household units compete in a wide array of input and output markets. These units display tremendous diversity in terms of their physical and human capital and natural resource endowments, production technologies, goals, and opportunity costs. Conceptualizing the full range of interactions among them as they simultaneously adjust to changing conditions is difficult.

Second, the available data have not offered a strong empirical foundation for observing relationships between causal factors and changes in aggregate farm structure. The principal resource has been the census of agriculture, which provides a detailed cross-sectional "snapshot" every 4 or 5 years but does not allow aggregate changes to be traced back to their origins in the management decisions of individual farmers. The link between firm-level responses and structural change, thus, cannot be readily observed.

Third, because of the complexity of the system, the lack of a clear theoretical guide, and the lack of suitable alternatives to cross-sectional time series data, most analysts have resorted to projection methods that seek merely to identify historical trends in farm structure and then carry them forward. Although such methods as age cohort analysis and nonlinear trend extrapolation have also been employed at times, the dominant methodology since the 1970's for U.S. farm structure projections has been the Markov chain with constant transition probabilities.

A fixed-probability, or stationary, Markov model cannot capture changes in the direction or pace of structural change due to varying causal factors. This paper explores the assumptions and implications of the stationary Markov model and then describes a nonstationary version of the same model that will allow conditional projections of change in the farm sector. As an example, a nonstationary model is estimated from longitudinal data from the census of agriculture for 1974-78. The nonstationary Markov model is then compared with a stationary model estimated from the same data to measure its relative accuracy in projecting structural change in U.S. agriculture for 1978-86.

This paper emphasizes an alternative approach to modeling changes in farm structure, one that allows for alternative futures for U.S. agriculture linked to different scenarios for change in economic conditions. This report, therefore, is more concerned with projection methods than projection results and projects farm numbers and sizes for the purpose of comparing the performance of alternative models rather than as actual forecasts of changes in U.S. farm structure.

THE STATIONARY MARKOV MODEL

A stationary (constant probability) Markov process is one in which individuals (such as firms or households) are distributed over a number of discrete "states" (such as income levels or number of acres operated) at a given time. These individuals then move among these states in a constant pattern over a fixed length of time, so that at the end of the time period, they have been redistributed among the states. Nothing interferes with the constant rate of

movements among states. All individuals are accounted for at the end of each time period, and each must be in only one state at a given time. The model, thus, allows the distribution of the individuals among the states to be predicted one or several time periods into the future, given only their starting distribution.

These ideas can be restated in mathematical form. The population of individuals is distributed as the vector S_t over the discrete and mutually exclusive states s_1, s_2, $\ldots s_n$ at time t. In applications to farm structure models, one state is usually defined as "not farming." This is the one to which exiters go and from which entrants come. The probability p_{ij} of an individual moving from state i at time t to state j at time t+1 depends only on the starting state i and not on any prior state or exogenous factor. Because it is a probability, p_{ij} must take a value between zero and one (the zero-one condition), and because all individuals must be located in one of the n states at time t+1 (even if it is the same state as before), the additional restriction $\Sigma p_{ij} = 1$ for all i is imposed (the row-sum condition).

The transition probabilities p_{ij} form the n-by-n transition probability matrix P, which transforms the distribution among states at time t (the 1-by-n vector S_t) into the distribution at time t+1 (S_{t+1}) via the relation $S_{t+1} = S_t P$.

The distribution after k periods is obtained by multiplying the initial state vector S_t by the stationary transition probability matrix raised to the k^{th} power. That is, $S_{t+k} = S_t P^k$. Another important feature of a stationary Markov process is that, over time, the system will converge to a dynamic equilibrium distribution S_e. The equilibrium distribution depends only on the transition probability matrix P and is independent of the initial distribution S_1. This implies that any two populations that can be represented by the same stationary Markov model should converge to the same proportional equilibrium distribution, differences in their beginning distributions notwithstanding.

In studies of U.S. farm structure, the states have usually been defined as intervals of acres operated, or gross sales, and the individuals as farm firms. The transition probabilities p_{ij} have been estimated in one of three ways. The first, developed by Krenz for his study of farm size in North Dakota, involves a procedure that manually "shifts" farms beginning from a given census size distribution to yield the distribution reported in the following census [12]. This is done under the assumption that farms will either stay the same size, grow, or exit. No provision is made for entry into farming or for existing farms to shrink in size.

The Krenz methodology was used to estimate the transition probability matrices used in the U.S. farm structure projections of the 1970's. Daly, Dempsey, and Cobb [7] constructed their model on the basis of the 1959 and 1964 Censuses of Agriculture, and Lin, Coffman, and Penn [14] based theirs on the 1964, 1969, and 1974 censuses.

A second approach is to estimate a stationary transition probability matrix from a time series of proportional distributions. This method, developed by Lee, Judge, and Takayama, uses restricted least squares regression to estimate the transition probabilities, with quadratic programming employed to minimize

the errors in predicted proportions subject to the zero-one and row-sum constraints [13]. This procedure also explicitly assumes stationary transition probabilities, although the authors do suggest methods for testing the validity of this assumption from the aggregate data [13, pp. 758-59]. It was used to estimate the transition probability matrix on which the OTA farm structure projections were based, using inflation-adjusted census data for 1969-82 [15, pp. 92-7].

A third procedure is possible when data on the size changes of individual farms are available for directly calculating the estimates of p_{ij} as $p_{ij} = n_{ij} / \Sigma_i n_{ij}$, where n_{ij} is the number of individuals moving from state i at time t to state j at time t+1. Transition probabilities estimated in this manner will by definition meet the zero-one and row-sum conditions. The third approach yields the most reliable estimates of the true transition probabilities over the interval studied, but the requirement of sufficient numbers of farm-level observations has, until recently, made this approach impossible at the U.S. level.

However, advances in linking individual farm records from successive censuses of agriculture have recently made a microdata-based approach to farm structure projections possible. Data on the reported farm size in both 1974 and 1978 of over 1.2 million farms were used as the basis for estimating a transition probability matrix for U.S. farm size in acres [8]. Structural projections were then made on the basis of the observed 1974-78 transition probabilities. Despite the greater confidence in the accuracy of the historical transition probability estimates offered by the microdata, projections of structure were still based on the assumption of transition probabilities that are constant thereafter.

The outcomes of the various methodologies for estimating transition probability are illustrated in table 1. Results are summarized for the three major U.S. farm structure projection studies discussed above [7, 14, 15] and an unpublished analysis [18] of 1974-78 census microdata on size by sales that follows the same methodology as that used in the Edwards, Smith, and Peterson study [8] of size by acres.3/ Projections of farm numbers by gross sales class for 1980, 1990, and 2000 are compared.

The wide range of the projections is apparent. For example, the projected number of farms with sales of $500,000 and above in the year 2000 ranges from 39,000 [7] to 226,000 [14]. As already discussed, there are a variety of possible explanations for the variance in the projections, from differences in the data on which they are based (and the inflation trends implicit in those data) to the transition probability estimation procedures used (and any assumptions about farm operator behavior implicit in these procedures). One element common to all the studies, however, is that structural change in agriculture is modeled as a stationary Markov process.

3/The results in [18] are based on the "maximum turnover" assumption, which is one of the two methods of estimating entry and exit rates used by Edwards, Smith, and Peterson [8, pp. 5-7].

Table 1--Comparison of Markov projections of U.S. farm structure

Year	Source (projection year)	Projection Basis	Farm size: Less than $20,000	$20,000-$99,999	$100,000-$199,999	$200,000-$499,999	$500,000 plus	Total Farms
					Thousands			
1974	Census [25]	n/a	1,513.1	646.1	101.2	40.0	11.4	2,311.8
1978	Census [26]	n/a	1,374.5	659.3	141.1	62.6	18.0	2,255.5
1980	Daly and others (1972) [7]	1959-64	1,388.5	447.5	45.5	24.0	13.0	1,918.5
	Lin and others (1980) [14]	1969-74	1,640.1	662.1	131.5	69.8	20.6	2,524.1
1982	Census [27]	n/a	1,355.3	581.6	180.7	93.9	27.8	2,239.3
1990	Lin and others (1980) [14]	1969-74	1,218.3	514.9	217.9	150.8	90.3	2,192.2
	OTA (1986) [15]	1969-82	991.6	486.8	126.2	144.2	54.1	1,802.9
	Census micro (1986) [18]	1974-78	1,301.1	689.6	177.2	90.0	27.3	2,285.2
1998	Census micro (1986) [18]	1974-78	1,294.9	693.3	181.6	93.8	28.8	2,292.4
2000	Daly and others (1972) [7]	1959-64	584.0	325.5	54.0	40.5	39.0	1,043.0
	Lin and others (1980) [14]	1969-74	928.7	350.3	167.5	190.1	225.8	1,862.4
	OTA (1986) [15]	1969-82	637.6	362.6	75.0	125.0	50.0	1,250.2

n/a= Not applicable.

Table 1, thus, highlights the major shortcoming of the stationary Markov approach to farm structure projections. Expectations based on the experience of the early 1960's failed to anticipate the inflation of the 1970's, and expectations formed in the 1970's apparently failed to incorporate the disinflation and financial stress of the 1980's. Assessing the accuracy of projections to 1990 and 2000 is at the moment impossible, yet their wide range clearly indicates that at least some projections will miss the mark rather

badly. Together, these facts suggest that the assumption of time-invariant transition probabilities in farm structure projections is not particularly useful.

AN ALTERNATIVE APPROACH TO MODELING FARM STRUCTURAL CHANGE

The remainder of this paper describes an alternative specification of the Markov model that allows conditional forecasts of structural change. A nonstationary Markov model, in which transition probabilities vary as a function of exogenous factors, is specified. However, a long time series of microdata on size changes of individual farms, from which transition probability functions could ideally be estimated, is not available. As an alternative, varying regional observations of transition probabilities in 1974-78 are treated as panel data from which relationships between hypothesized causal factors and structural change might be estimated. The resulting nonstationary model is then tested against a stationary Markov model, derived from the same data, by comparing the projection accuracy of the two models over 1978-86.

A Nonstationary Markov Model

A nonstationary Markov process is one in which the probability of movement, p_{ij}, can vary over time. The nonstationary transition probability, thus, is denoted $p_{ij(t)}$, with (t) the time period of the transition. (Specifically, (t) is the time period beginning at time t and ending at time t+1.) The transition probability varies over time in relation to exogenous factors, in contrast to the stationary case in which it is assumed to be unaffected by them. Generally, the probability of transition among states might be described as dependent on the set of n exogenous factors X_1, X_2, ...X_n, where $p_{ij(t)} = f(X)$. As before, the zero-one and row-sum conditions must hold for all $p_{ij(t)}$.

The nonstationary transition probabilities together form the nonstationary transition probability matrix $\mathbf{P}_{(t)}$. The distribution of the population among states $\mathbf{S}_t$ is now transformed into the distribution $\mathbf{S}_{t+1}$ by the operation $\mathbf{S}_t\mathbf{P}_{(t)}$. The distribution $\mathbf{S}_{t+k}$ is obtained by multiplying the initial state vector $\mathbf{S}_t$ by the product of the k transition probability matrices $\mathbf{P}_{(t)}$, $\mathbf{P}_{(t+1)}$, ... $\mathbf{P}_{(t+(k-1))}$.

Because the transition probability matrices are not necessarily equivalent from one time period to the next, raising the initial nonstationary transition probability matrix to the power of the number of time periods does not yield the same result as the period-by-period multiplication of the current population distribution by the transition probabilities. This also means that the system will not necessarily converge to an equilibrium distribution.

The nonstationary Markov model has been employed in several instances to depict particular components of change in the farm sector. These applications have been based on different methods of estimating transition probability functions.

The simplest nonstationary model is that developed by Salkin, Just, and Cleveland [17], which represented size transitions by Oklahoma cotton warehouses as two different functions of time. A simple linear function, of which the stationary Markov process is simply a special case with all time coefficients set equal to zero, meets the row-sum requirement but violates the zero-one probability limits after some number of time periods. A geometric model, with the magnitude of change over time falling at a constant rate, had somewhat better properties, although zero-one probability bounds are not necessarily satisfied under this approach either. However, as the authors point out, a more fundamental shortcoming of the time-dependent approach is that it fails to reflect "the exogenous forces which actually influence the transition probabilities" [17, p. 81]. In this respect, the time-dependent Markov model does not mark a significant departure from the stationary case.

A second approach, developed by Hallberg, is to estimate a function for each row of the transition matrix, with exogenous economic factors as the independent variables [9]. In order to ensure that the resulting matrix will conform to the row-sum condition, intercept terms must be constrained to sum to one and the coefficients of the exogenous variables must sum to zero. Yet, this approach still does not ensure that individual transition probabilities will remain within the zero-one range. In his study of the Pennsylvania milk manufacturing industry, Hallberg had to resort to ad hoc procedures to keep the predicted probabilities within the permissible range.

A third approach that has appeared in the literature is to construct a nonstationary transition probability matrix based on a multinomial logit function [20]. This method by Stavins and Stanton meets the row-sum and zero-one conditions under all circumstances and offers the additional advantage of permitting a different set of explanatory factors for each cell of the transition matrix. When compared with alternative methods of projecting (known) future distribution of New York dairy farms outside the sample set, including stationary Markov analysis, trend analysis, and negative exponential functions, the multinomial logit-based nonstationary Markov model performed the best [21]. The multinomial logit function, therefore, was chosen as the basis for the model constructed here. The following section describes the function in greater detail.

A Multinomial Logit Function

A logit function is based on the cumulative logistic probability function and takes the general form:

$$p_j = f(\alpha + \beta X_j) = \frac{1}{1 + \frac{1}{e^{\alpha + \beta X_j}}} \qquad (1)$$

where p_j is the probability of the event j given the set of exogenous values X_j.4/ The logistic function yields a probability distribution similar to the normal but with slightly fatter tails.

4/The entire discussion of logit models draws heavily on [16, pp. 287-310].

A linear relationship between the probability of event j (p_j) and the factors that influence it (X_j) can be derived by rewriting the logistic function and taking natural logarithms of both sides [16, pp. 287-9]. This yields

$$\ln \left(\frac{p_j}{1 - p_j}\right) = \alpha + \beta X_j \ . \qquad (2)$$

Equation (2) is a logit function, where $\ln \left(\frac{p_j}{1 - p_j}\right)$ is the natural log of the odds ratio, or "logit," of p_j.

In the case where only two outcomes, event j and event d (a binomial model), are possible, $p_j + p_d = 1$ and $p_d = 1 - p_j$, so equation (2) can also be written as:

$$\ln \left(\frac{p_j}{p_d}\right) = \alpha + \beta X_j . \qquad (3)$$

A logit function relating the log odds of event j to the values of its causal factors X_j can be estimated as in equation 3. Once the parameters of equation 3 have been estimated, the equation can be used to predict the probability of event j under varying values of the causal factors. Let X_{j*} be a particular set of values of the causal factors of event j. The predicted logit of j is then given by:

$$\text{est} \left[\ln \left(\frac{p_j^{*}}{p_{d*}}\right) \right] = \hat{\alpha} + \hat{\beta} X_{j}{*} . \qquad (4)$$

Equation 4 can be converted to the predicted ratio of p_j to p_d by raising base e to the predicted logit. An additional adjustment is needed, however, to produce an unbiased estimate of the predicted ratio p_j/p_d. This is because simply taking the antilog of predicted value $\hat{\alpha} + \hat{\beta} X_j{*}$ will give the median value, rather than the mean, of the predicted logit p_j/p_d. To reduce this bias, Dadkhah [6] suggests estimating the predicted value of $\ln (p_j/p_d)$ as $\hat{\alpha} + \hat{\beta} X_j{*} + 0.5s^2$, where s^2 is the variance of prediction of the estimated logit function. With this correction added, the predicted ratio of p_j to p_d can be obtained:

$$\text{est} \left(\frac{p_{j*}}{p_{d*}}\right) = e^{\hat{\alpha} + \hat{\beta} X_j{*} + 0.5s^2} . \qquad (5)$$

To solve for the predicted probability of event j under the particular set of exogenous values X_{j*}, the value of the predicted denominator $\hat{p}_{d*}$ can be obtained:

$$\hat{p}_{d*} = \frac{1}{1 + \text{est}\left(\frac{p_{j*}}{p_{d*}}\right)} . \qquad (6)$$

The predicted probability of event j can then be solved by multiplication:

$$\hat{p}_{j*} = \hat{p}_{d*} \cdot \text{est}\left(\frac{p_{j*}}{p_{d*}}\right) . \qquad (7)$$

The form of the logistic function ensures that the predicted probabilities p_j and p_d will always take on values between zero and one. The two predicted

probabilities will also sum to one. The logit model can be extended to cases with more than two outcomes (a multinomial logit model). With n possible outcomes, logit functions for n-1 of them can be estimated similarly to equation 3:

$$\ln\left(\frac{P1}{Pd}\right) = \alpha_1 + \beta_1 X_1 \tag{8}$$

$$\vdots$$

$$\ln\left(\frac{Pj}{Pd}\right) = \alpha_j + \beta_j X_j$$

$$\vdots$$

$$\ln\left(\frac{Pn}{Pd}\right) = \alpha_n + \beta_n X_n$$

for all $j \neq d$.

Once the parameters of the system have been estimated, they can be used to predict the logits of the probabilities as in equation 4, given the particular set of exogenous values X_n*:

$$\text{est}\left[\ln\left(\frac{P1*}{Pd*}\right)\right] = \hat{\alpha}_1 + \hat{\beta}_1 X_1* \tag{9}$$

$$\vdots$$

$$\text{est}\left[\ln\left(\frac{Pj*}{Pd*}\right)\right] = \hat{\alpha}_j + \hat{\beta}_j X_j*$$

$$\vdots$$

$$\text{est}\left[\ln\left(\frac{Pn*}{Pd*}\right)\right] = \hat{\alpha}_n + \hat{\beta}_n X_n*$$

for all $j \neq d$.

The predicted logits are then converted to ratios as in equation 5, again adding the correction for variance suggested by Dadkhah [6]:

$$\text{est}\ \left(\frac{p_1*}{p_d*}\right) = e^{\hat{\alpha}_1 + \hat{\beta}_1 X_1* + 0.5 s_1^2} \tag{10}$$

$$\vdots$$

$$\text{est}\ \left(\frac{p_j*}{p_d*}\right) = e^{\hat{\alpha}_j + \hat{\beta}_j X_{j*} + 0.5 s_j^2}$$

$$\vdots$$

$$\text{est}\ \left(\frac{p_n*}{p_d*}\right) = e^{\hat{\alpha}_n + \hat{\beta}_n X_n* + 0.5 s_n^2}$$

for all $j \neq d$.

The predicted value of the denominator event p_d* can be solved similarly to equation 6:

$$\hat{p}_{d*} = \frac{1}{1 + \sum_{j \neq d}^{n} \text{est}\left(\frac{p_j*}{p_d*}\right)}. \tag{11}$$

The remaining predicted probabilities can then be derived as in equation 7:

$$\hat{p}_{j*} = \hat{p}_{d*} \cdot \text{est}\left(\frac{p_j*}{p_d*}\right) \tag{12}$$

for all $j \neq d$.

The predicted probabilities will all fall between zero and one and sum to one, just as in the binomial case.

The multinomial logit function, thus, is a useful vehicle to represent the range of possible size changes of farms over time, given their starting size. For example, let $p_{1j(t)}$ be the observed probability of a farm moving from size class 1 to size class j in time period (t). The set of exogenous factors $X_{1j(t)}$ is hypothesized to affect the probability of movement. Modeling this as a multinomial logit function gives the relation:

$$p_{1j(t)} = \frac{1}{1 + \frac{1}{e^{\alpha_{1j} + \beta_{1j} X_{1j(t)}}}} \tag{13}$$

Given a time series of observed transition probabilities and hypothesized causal factors, a nonstationary Markov model can be estimated. One, therefore, can estimate n-1 functions of the form:

$$\ln\left(\frac{p_{1j(t)}}{p_{1d(t)}}\right) = \alpha_{1j} + \beta_{1j} X_{1j(t)} \tag{14}$$

for all $j \neq d$, where $\ln(p_{1j(t)}/p_{1d(t)})$ is the logit of $p_{ij(t)}$, and $p_{1d(t)}$ is

the denominator event. Once the n-l functions have been estimated, estimated values for the n-l ratios $\ln(p_{1j(t)}/p_{1d(t)})$ can be obtained by inserting values for the exogenous variables. After adding the correction for variance, the logits can be converted to ratios as in equation 10. From these estimates, the value of the denominator transition probability $p_{1d(t)}$ can be estimated as in equation 11, and then the remaining n-l transition probabilities can be predicted as in equation 12.

The predicted values $\hat{p}_{1j(t)}$, thus, will meet the restrictions $\Sigma_j \hat{p}_{1j(t)} = 1$, and $0 < \hat{p}_{1j(t)} < 1$ for all j.

For the normalization required to estimate the function, all observed $p_{ij(t)}$ are required to be greater than zero. This requirement apparently does not raise particular problems for the kind of application considered here, given the theoretical, although highly unlikely, possibility that farms move between the largest and smallest size classes in a single period. A separate multinomial logit function can be estimated for each row of the transition probability matrix. This model meets all the mathematical requirements for a nonstationary Markov process, while allowing economic analysis of the effects of exogenous factors on size transition probabilities. The model is also flexible in that the specification of each individual transition probability function can be different for each element of the matrix. Thus, varying combinations of factors can be included to predict the growth or shrinkage of farms beginning from different sizes.5/

5/In the multinomial case, the choice of denominator event can affect the model's predicted probabilities in two ways. The first is simply through differences in the specification of exogenous variables that can arise depending on which event's logit is excluded (as the denominator) in the estimation phase. Thus, the choice of denominators can affect the selection of exogenous variables that drive the model. Second, models with the same sets of exogenous variables can also differ somewhat according to the choice of denominators. As an experiment, row seven of the transition probability matrix (corresponding to farms with initial sales of $40,000-$99,999) was estimated first with the denominator event set as p_{77} (where i=j, or the probability of remaining in the same size class) and then with the denominator set at p_{71} (j=1, or the probability of exiting). For events other than p_{71} or p_{77}, the same exogenous variables were used to estimate each individual logit function in both cases. For the two alternative denominator events, the exogenous variables for the logits were unchanged between the two as the denominator changed. The two resulting models for row seven produced different predicted probability distributions given the same values of the exogenous variables. These differences were relatively small in predicting within the 1974-78 sample period but increased for out-of-sample predictions. In the model estimated later in this paper (table 5), the event p_{ij} (i=j, the diagonal cells of the matrix) is used as the denominator for each row. A more systematic means of evaluating the effects of different denominators and choosing the most appropriate one would help in developing the "best" nonstationary Markov model of structural change, but that is beyond the scope of this paper.

AN APPLICATION: A NONSTATIONARY MARKOV MODEL OF U.S. FARM STRUCTURE

In this section, a nonstationary Markov model of U.S. farm structure is estimated, with the rows of the transition probability matrix represented by multinomial logit functions. Because a time series of directly observable transition probabilities is unavailable, longitudinal microdata from the 1974 and 1978 Censuses of Agriculture are grouped by geographic region and used as panel data from which to estimate transition probability functions.

The Data

The data set used in this analysis consists of 1.2 million longitudinal records from the 1974 and 1978 Censuses of Agriculture. It was constructed by linking the two census files by means of respondent identification codes originally designed for managing mailing lists. Records carrying the same identification code in both censuses were linked to provide information on size changes on individual farms continuing in the censuses for 1974-78. Continuing farms, therefore, are defined as those continuing under the same management.

The records for some farmers continuing in operation during 1974-78 likely were not matched in the census files and, thus, were excluded, and other records likely were matched and included when, in fact, the operator had changed. Nevertheless, the data base is the most detailed yet available on changes in individual U.S. farms over time. Thus, the data base makes possible the most accurate estimates yet available of farm size transition probabilities in a given time and place. The data set and its construction are described in greater detail in [8].

In this study, data on the total value of agricultural products sold in 1974 and 1978 were used to construct transition probability matrices for farms moving among size classes. Nine different size classes (states) were defined, ranging from less than $2,500 to $500,000 and more. Data for both years are in nominal dollars.6/

A 10th state was defined as "nonfarm," to which exiters go and from which new entrants come. Entrants and exiters during 1974-78 are not precisely identifiable as such in the longitudinal file due to the possibility of some incorrect or missed record matches. Therefore, for this analysis, entry and exit probabilities were estimated under the assumption that the longitudinal file was a complete count of all farms continuing under the same management during 1974-78. Thus, any farms counted in the 1974 census that failed to show up in the linked 1974-78 longitudinal file, and for which the actual 1974-78 behavior is unknown, are assumed to have exited. Likewise, any farms counted in the 1978 census but not matched in 1974-78 are assumed to have been new entrants.

6/At the time this analysis was completed, census data for 1982 had not yet been linked to the 1978 census records to form a data base for 1978-82 comparable to that for 1974-78. Thus, the model is estimated only from data covering 1974-78.

Given these assumptions, the probability of exit from a given 1974 size class can be estimated simply as the proportion of farms failing to reappear in the census of 1978. However, estimating the probability of entry from the number of "new" farms in 1978 is more difficult. In the case of entry, the divisor with which to estimate probabilities is not obvious as it is in the case of continuing or exiting farms because it requires an assumption about the initial size of the "nonfarm" population.

Assumptions about the size of the nonfarm population can affect the results of Markov analysis. Stanton and Kettunen [19] show that the number of farms at equilibrium is positively related to the size of the nonfarm population but that the magnitude of the effect diminishes as the size of the assumed nonfarm population increases. Edwards, Smith, and Peterson, in a study of farm size by acreage based on the same longitudinal data file used here, found little sensitivity to choices above 5 million potential entrants [8]. Five million, thus, was chosen as the assumed initial size of the "nonfarm" population, and entry probabilities were estimated on that basis.

Tables 2 and 3 provide an example of how transition probability matrices were estimated from the 1974-78 longitudinal census data. Data are for the United States. The boldfaced data in table 2 show the cross-classification of the longitudinal farms by their 1974 and 1978 gross sales levels. The published census totals of farm numbers by sales class in 1974 and 1978 are the row and column sums, respectively (in normal typeface). The remaining numbers for entrants and exiters, denoted by an underline, are then derived by subtraction of the longitudinal farms from the census total for the year.7/ Finally, the assumed 5 million "nonfarms" (marked with an asterisk) are placed in the entry row total cell for 1974. The transition probability matrix is then computed by dividing the cell counts by the row sums and is shown in table 3.

Regional Transition Probability Matrices, 1974-78

Estimation of a nonstationary Markov model built on multinomial logit functions ideally requires a time series of observed transition probabilities. Such a data set is currently unavailable. This section evaluates regional-level transition probabilities for 1974-78 as a substitute. The implications for regional transition probabilities of the stationary Markov assumption are explored, and the regional data are then analyzed to determine whether or not they are consistent with those assumptions.

The assumption of stationary transition probabilities, where $p_{ij}(t) = p_{ij}(t+1)$ for all i,j, and t, implies that the only factor affecting the size class into which a farm moves is the size from which it starts. The time period of the movement, with its particular configuration of exogenous factors, such as prices and opportunity costs, is assumed to have no effect on the probability of growth, shrinkage, or exit. The other attributes of the farm aside from size, such as the personal characteristics of the operator, where he or she

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7/The explicit assumption that farms not included in the longitudinal data set, for which the actual behavior is unknown, were entrants and exiters in 1974-78 is reflected by the zeros in the "unknown" categories in both 1974 and 1978. The "unknown" category is then dropped from table 3 for simplicity.

Table 2--Cross-classification of gross sales, 1974-78, census total farms 1974 and 1978, and derived entries and exits

1974 sales	State	1978 sales: 0 (exit) (1)	Less than $2,500 (2)	$2,500-4,999 (3)	$5,000-9,999 (4)	$10,000-19,999 (5)	$20,000-39,999 (6)	$40,000-99,999 (7)	$100,000-199,999 (8)	$200,000-499,999 (9)	$500,000 and over (10)	Unknown	1974 total
						Farm numbers							
0 (entry)	1	3,944,779	278,364	153,639	146,322	130,980	124,398	138,837	48,390	25,274	9,017	0	5,000,000#
Less than $2,500	2	371,873	126,642	73,427	46,081	19,129	7,095	3,653	1,042	424	82	0	649,448
$2,500-4,999	3	133,665	24,835	33,248	37,109	18,831	6,313	2,532	522	174	34	0	257,263
$5,000-9,999	4	147,634	15,923	22,858	44,914	41,364	16,486	5,826	1,016	296	56	0	296,373
$10,000-19,999	5	147,158	8,360	10,828	25,437	52,271	46,366	16,731	2,233	551	76	0	310,011
$20,000-39,999	6	138,570	3,866	4,410	9,935	26,717	67,030	63,346	6,566	1,178	153	0	321,771
$40,000-99,999	7	119,156	1,968	1,788	3,541	8,499	28,153	110,893	44,007	5,892	413	0	324,310
$100,000-199,999	8	31,908	451	379	555	1,130	2,739	16,187	31,850	15,012	942	0	101,153
$200,000-499,999	9	15,325	103	109	175	262	533	1,945	5,148	12,819	3,615	0	40,034
$500,000 and over	10	6,234	23	13	19	32	62	143	276	1,025	3,585	0	11,412
Unknown 1/		0	0	0	0	0	0	0	0	0	0	0	0
1978 Total		n/a	460,535	300,699	314,088	299,215	299,175	360,093	141,050	62,645	17,973		

Numbers in bold typeface = Census longitudinal file.

Numbers in regular typeface = All farms, 1974 and 1978 census.

Underlined numbers = Derived from text.

= Assumed number of potential entrants in 1974.

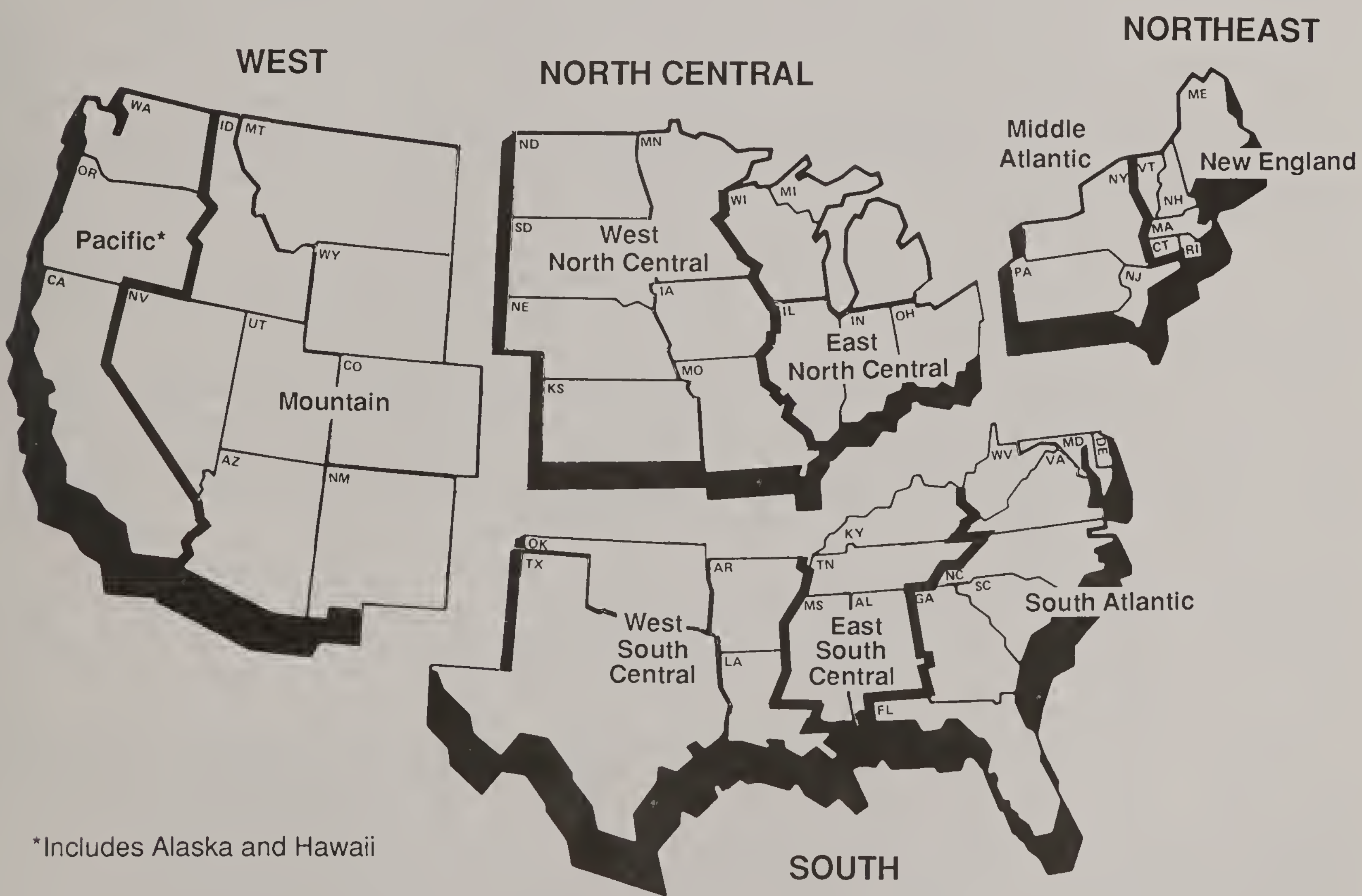
1/Unknown refers to those farms not captured in the longitudinal data set. In this analysis, all farms reported in the 1974 and 1978 censuses and not captured in the longitudinal data set are assumed to have exited and entered over the period. Thus, the number of farms for which the 1974-78 movement is unknown is assumed to be zero.

Table 3--Transition probability matrix, U.S. farms by gross sales, computed from table 2 1/

Item	i=	p_{i1} j= 1	p_{i2} 2	p_{i3} 3	p_{i4} 4	p_{i5} 5	p_{i6} 6	p_{i7} 7	p_{i8} 8	p_{i9} 9	p_{i10} 10	$\Sigma_j p_{ij}$ Row sum
p_{1j}	1	0.7890	0.0557	0.0307	0.0293	0.0262	0.0249	0.0278	0.0097	0.0051	0.0018	1
p_{2j}	2	.5726	.1950	.1131	.0710	.0295	.0109	.0056	.0016	.0007	.0001	1
p_{3j}	3	.5196	.0965	.1292	.1442	.0732	.0245	.0098	.0020	.0007	.0001	1
p_{4j}	4	.4981	.0537	.0771	.1515	.1396	.0556	.0197	.0034	.0010	.0002	1
p_{5j}	5	.4747	.0270	.0349	.0821	.1686	.1496	.0540	.0072	.0018	.0002	1
p_{6j}	6	.4306	.0120	.0137	.0309	.0830	.2083	.1969	.0204	.0037	.0005	1
p_{7j}	7	.3674	.0061	.0055	.0109	.0262	.0868	.3419	.1357	.0182	.0013	1
p_{8j}	8	.3154	.0045	.0037	.0055	.0112	.0271	.1600	.3149	.1484	.0093	1
p_{9j}	9	.3828	.0026	.0027	.0044	.0065	.0133	.0486	.1286	.3202	.0903	1
p_{10j}	10	.5463	.0020	.0011	.0017	.0028	.0054	.0125	.0242	.0898	.3141	1

1/ p_{ij} = probability of movement from state i to state j, 1974-78.

Figure 1- Census Divisions



*Includes Alaska and Hawaii

lives, or what else he or she does, also is assumed to have no effect on the transition probability. The stationary assumption, thus, seems to imply that observed transition probabilities should be the same across distinct geographic areas over a given time period, as well as constant from one period to the next.

The reasonableness of the assumptions of the stationary Markov model can be tested by examining distinct regional transition probability matrices for 1974-78. Nine separate matrices were computed, one for each census division (fig. 1). They were derived from the census microdata longitudinal file using the methodology of table 2, with the U.S. total of 5 million potential entrants in 1974 apportioned by division according to the proportion of total U.S. farms in the division in 1974. The nine computed transition probability matrices are listed in the appendix.

Stationary transition probabilities can be tested for in several ways. Anderson and Goodman [1] present a formal statistical test of the hypothesis that the $p_{ij(t)}$ are constant over all T time periods. It is a chi-square test, with the test statistic computed as

$$-2\ [\Sigma_i\Sigma_j\Sigma_t m_{ij(t)} \ln p_{ij(\cdot)} - \Sigma_i\Sigma_j\Sigma_t m_{ij(t)} \ln p_{ij(t)}],$$

where $m_{ij(t)}$ is the number of individual observations on which the estimated transition probability $p_{ij(t)}$ is based, and $p_{ij(\cdot)}$ is the average transition probability over all time periods. It is distributed as chi-square with $(T-1)(n-1)n$ degrees of freedom, with T the total number of time periods and n the number of states.

A test of the hypothesis that the transition probabilities were equal across the nine census divisions in 1974-78 can be made by applying the Anderson-Goodman test as above with (t) denoting the geographic region and (·) the U.S. totals as in table 2.8/ Computed in this way, the value obtained for the test statistic is 38,833. This compares with a critical value for chi-square at the 99-percent confidence level and 720 degrees of freedom of 810.4.9/ Thus, the null hypothesis that transition probabilities were the same in all nine regions during 1974-78 is rejected by a wide margin.

Regional variability in transition probabilities can also be assessed more informally. Table 4 summarizes the variability among census divisions by

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8/The test breaks down cases in which some observed transition probabilities are zero. This was true for a few cells in some of the regional matrices, although the U.S. level had no zero cells. In these cases, the zero probabilities were converted to 0.000001.

9/The degrees of freedom for the test are calculated as follows: T=9 (number of regions), n=10 (number of states). Degrees of freedom = $(T-1)(n-1)n = 720$. The critical value for chi-square is calculated as $0.5[(Z_\alpha + (2v-1)^{.5}]^2$, where Z_α is the alpha point (probability of rejecting the null hypothesis when it is true) of the standardized normal distribution and v is the degrees of freedom [20, p. 24].

Table 4--Matrix of coefficients of variation of observed transition probabilities, nominal sales for 1974-78, and nine census divisions 1/

	i=	Pi1	Pi2	Pi3	Pi4	Pi5	Pi6	Pi7	Pi8	Pi9	Pi10
		j= 1	2	3	4	5	6	7	8	9	10
P1j	1	2.8	40.0	28.1	14.2	9.5	26.5	32.1	24.7	43.4	105.5
P2j	2	6.1	13.1	10.9	19.0	25.6	34.3	42.1	33.9	45.9	70.1
P3j	3	5.1	16.1	10.1	9.8	17.9	27.5	31.5	36.6	55.9	72.7
P4j	4	4.4	24.4	10.4	9.4	8.9	18.2	24.9	33.9	53.9	91.9
P5j	5	5.0	37.5	21.0	6.9	8.5	14.3	17.1	28.7	57.1	87.6
P6j	6	6.9	54.4	37.3	20.6	11.2	11.7	17.5	26.0	59.6	69.9
P7j	7	12.3	69.6	62.3	41.0	20.0	22.9	16.6	9.9	33.1	84.3
P8j	8	15.5	72.7	59.0	46.2	34.2	22.2	25.5	14.0	10.9	37.1
P9j	9	7.0	62.1	64.1	46.6	31.4	29.1	23.3	17.9	11.1	20.5
P10j	10	5.8	46.0	117.3	101.2	58.1	48.9	46.1	38.9	17.2	13.3

1/The coefficient of variation is calculated as the sample standard deviation divided by the sample mean times 100.

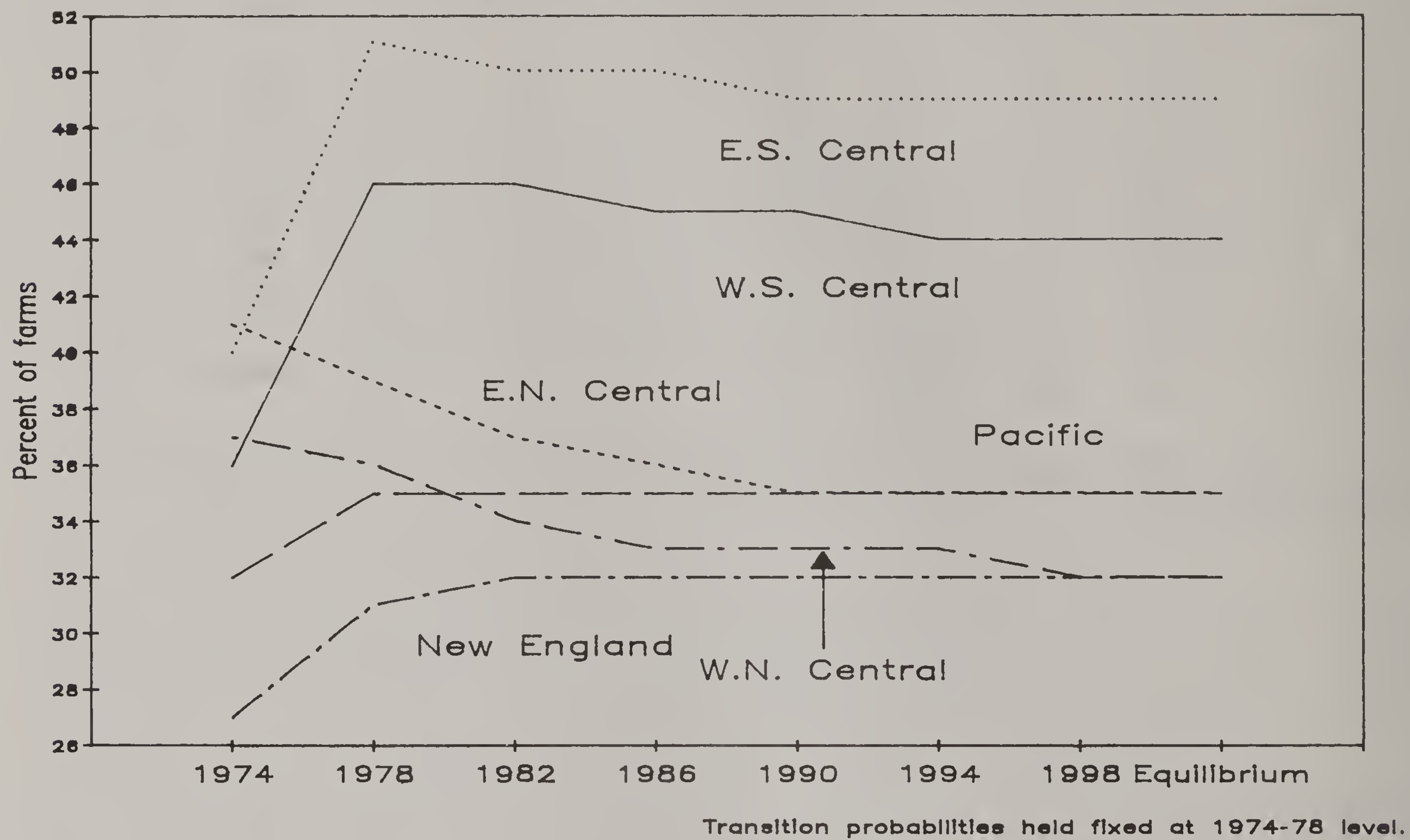
reporting the coefficient of variation (the standard deviation as a percentage of the mean) of each cell in the transition probability matrix. The weighted means of the p_{ij}'s used as the denominators are the same as those calculated directly from the U.S. level data in table 2.

The 1974-78 transition probabilities exhibit a wide range of values. For example, p_{51}, the observed probability that a farm with sales of $10,000-20,000 in 1974 would exit by 1978, ranged from 0.43 to 0.53. And $p_{9,10}$, the probability of movement from the $200,000-500,000 class into the $500,000 and over class, nearly doubles from the lowest to highest observed values (0.069 to 0.121).

A third way to look at regional differences in 1974-78 transition probabilities is to calculate the proportional distributions of farms over time and at equilibrium if the observed transition probabilities are held constant. As an illustration, projected time paths for six of the nine census divisions are depicted for small farms (gross sales of $2,500-19,999) in figure 2. The regional transition probability matrices imply quite different results from one another. Two project a sharp increase in the proportion of small farms in 1974-78, followed by a gradual decline to an equilibrium level well above that of 1974. Two others imply a steady decline, to an equilibrium level below that of 1974. And, two others yield an increase in 1974-82 and a constant proportion afterward. The observed regional patterns of structural change in 1974-78 were clearly headed in different directions.

Viewed from these three perspectives, regional-level observations of 1974-78 transition probabilities do not support the assumptions of a stationary Markov process. The probability of a farm starting from a given size class growing, shrinking, or exiting in 4 years varied significantly from one region to the next. Thus, seeking an explanation for these varying probabilities in the particular economic characteristics of each region seems logical. The next section presents nonstationary transition probabilities modeled as multinomial logit functions, estimated from the nine regional transition probability matrices for 1974-78.

Figure 2. Comparison of Stationary Markov Paths. Projected Proportion of Farms with Sales $2,500-$19,999 by Census Division, 1974 to Equilibrium



Transition Probability Functions for U.S. Farms by Gross Sales

Following the procedures outlined above, a nonstationary Markov model was estimated for U.S. farms by gross sales class from nine regional observations of 1974-78 transition probabilities. The observed p_{ij}'s were converted to their logits, using the diagonal cells of the transition probability matrix (p_{ij}, where i=j) as the denominator. The logits were then regressed on exogenous variables as in equation (14) to estimate transition probability functions.

A large body of literature discusses the causes of structural change in U.S. agriculture. Babb [3] summarizes important factors, including variations in input and output prices among farms of different sizes, technological change, size economies, risk, price-cost margins, exchange arrangements, capital requirements that affect entry, government policies, and farm operator characteristics, such as management ability, goals, and alternative opportunities.

Babb cites a number of factors, such as technological change and government policies, that cannot be examined easily in the context of the data set used here. Technology and government programs are assumed to be equally available in all regions at a given time. Other factors, such as regional differences in farm operators' characteristics and farm and nonfarm prices, are observable as possible sources of differences in rates of structural change, however.

These factors, along with their hypothesized relationships to farm entry, exit, growth, and decline, are listed in table 5.

The age distribution of the existing operator population is assumed to affect aggregate rates of structural change. An older population of operators is likely to have higher rates of exit due to retirement. Age is also expected to be negatively related to the likelihood of farm growth, as older operators move past the expansion phase of the firm life cycle toward consolidation and preparation for exit.

The extent of off-farm work by existing operators is hypothesized to be both a symptom of more fundamental underlying forces and a causal factor in its own right. Multiple jobholding in U.S. agriculture is generally seen as a response to low farm incomes, particularly on smaller and midsized farms. Viewed this way, off-farm work is likely to be associated in the long run with higher rates of both exit growth and farm growth, as operators move out of agriculture altogether or expand to a farm size sufficient to generate adequate income. Shortrun effects of off-farm work may be quite different, however. Off-farm work may impede exit as long as operators can earn sufficient total income from the combination of sources. It may also lead to farm size declines as operators devote more labor to higher paying off-farm work. Off-farm work by existing operators is unlikely to affect directly the rate of entry by new operators, however. Thus, while off-farm work and the factors that underlie it are likely to be important forces in farm structural change, making a priori judgments of the likely empirical relationship to 1974-78 transition probabilities is difficult.

Because the data used in the analysis are in nominal dollars, increases in farm product prices are expected to be positively associated with farm growth

Table 5--Some possible sources of regional differences in farm size (gross sales) transition probabilities

Variable	Hypothesized relation to: Entry	Exit	Growth	Shrinkage
Age of existing operator population	+*	-	+	
Extent of off-farm work by existing operator population	+/-	+*/-	+/-	
Change in farm product prices	+	-	+	-
Change in farm asset prices	-			
Change in nonfarm incomes (opportunities)	-	+	+/-	+*/-

*Starred entries were not rejected in the estimation results reported in table 6.

and negatively associated with shrinkage. Thus, inflation is assumed to be reflected in apparent rates of farm structural change. All other things equal, higher farm product prices are also likely to be associated with higher rates of entry and lower rates of exit, as higher commodity prices induce more entrants to farming and keep farming more attractive to those who might otherwise leave.

The value of farm assets, chiefly land, is hypothesized to be negatively related to operator entry. Higher land prices, especially if also reflected in lease rates, have been widely thought to pose barriers to entry. The effects on exit or the performance of continuing farms is much more uncertain. In times of increasing farm asset values, as in 1974-78, the potential for capital gains resulting from farmland appreciation may induce some operators to sell their assets and exit, while inducing others with the additional cushion of equity they need to remain in farming. The likely effect of rising farm asset values on exit rates is unclear. The same is true of impacts on farm expansion or contraction. Generally higher prices for farm assets (whether reflected in sale prices or rents) can both propel and deter farm expansion by simultaneously increasing some farmers' net worth and raising the costs of expansion to all. The net relationship between changes in asset values and farm growth or shrinkage will depend on a number of factors unique to each farm firm, including operator expectations, attitudes toward risk, and capital structure, none of which can be captured in the highly aggregated data used here. Thus, no hypothesized relationship between asset values and aggregate rates of growth or shrinkage can be offered.

Finally, because farming is a relatively minor activity in relation to the entire labor market, even in heavily agricultural areas, the opportunity cost of farming is hypothesized as a major cause of structural change. Changes in nonfarm incomes are assumed to be related negatively to entry and positively to exit as the "pull" of improving nonfarm opportunities causes would-be farmers to choose other employment and induces other farmers to leave for other work. Similar to the effects of off-farm work, nonfarm incomes might have offsetting impacts on continuing farms. In the long run, rising nonfarm incomes may contribute to increasing farm size as improving opportunities off the farm raise the minimum farm income (and, thus, farm size) necessary to hold workers in farming [11]. Over the short term, however, operators able to adjust their own labor allocation between the farm and nonfarm sectors might choose to reduce their farm size in order to begin or increase off-farm employment. Rising nonfarm incomes may be either positively or negatively related to farm growth.

Regression Results

The logits of the observed 1974-78 transition probabilities were regressed on variables representing the above hypothesized causal factors, as in equation (14). The 10 rows of the transition probability matrices were normalized by their diagonal cells. Thus, a total of 10x(10-1)=90 equations were estimated. All transition probability functions were estimated by an ordinary least

squares regression (OLS) from the nine regional observations weighted by the number of farms in the region and size class in 1974.10/

Data on the hypothesized causal factors were developed for each region or region and sales class. The age of the operator population in 1974 was characterized as the proportion of operators aged 65 and older in each sales class and region. Off-farm work was measured as the proportion of operators in the sales class and region working off the farm 200 days or more per year. Changes in farm product prices for 1974-78 were measured separately for each region, by weighting the U.S. indices of prices received by farmers for crop and livestock products by 1974 regional crop and livestock sales. Changes in farm asset prices were computed as the index of change in the total value of farm real estate in the region for 1974-78. And nonfarm incomes were measured as the index of change in regional nonfarm personal income per capita for 1974-78.

For many cells of the transition probability matrix, the independent variables considered had little or no explanatory power. This was especially true of cells in which the mean transition probability was extremely low and the variance correspondingly large (see table 3 for the range of variation across the observed transition probability matrices and [16, p. 293] for a general discussion of this problem). The fit was also poor for all cells representing entry and the behavior of very small farms. This was not unexpected, given that only nine observations were available, the resulting heterogeneity of the geographic regions used, and the lack of data on potential entrants on which to base entry probabilities.

10/Because the transition probabilities in any one row are functionally related (an increased probability of growth equates to a decreased probability of staying the same size or shrinking, for example), the cross-equation error terms in each row are expected to be correlated. This suggests that more efficient estimates of the parameters might be obtained by estimating all nine equations for each row of the matrix simultaneously, using a generalized least squares (GLS) regression [16, pp. 347-49]. An OLS regression was used instead, on both theoretical and practical grounds. While equation-by-equation OLS regression yields parameter estimates that are not efficient (minimum variance) in systems of equations in which the dependent variables are correlated, OLS still yields unbiased estimates of those parameters (that is, the expected value of the parameter estimate is the true value for the population). Thus, the OLS significance levels for the estimated coefficients are on the conservative side. In applications such as this one, the precise significance level of the individual parameter estimates in each equation is not of primary interest. It is used only as one criterion to judge among alternative specifications for each cell. A more practical reason for the choice of OLS over GLS regression is ease of computation. With nine equations for each row of the matrix, even the limited number of exogenous variables considered here leaves a large number of possible combinations. Rather than re-estimate all nine equations for each row every time the specification of one cell equation was changed, individual transition probability functions were estimated and selected on the basis of providing the best possible fit (in terms of OLS regression coefficients significant at 0.10 or less) for that cell. This made estimation of the model much less cumbersome.

Significant results were obtained for somewhat larger farms, however, with annual sales of between $5,000-500,000. The proportion of operators aged 65 or older in 1974 was positively associated with the probability of exit by 1978. This relationship was particularly strong among farms with initial sales of $20,000-499,999, and is consistent with theoretical expectations.

Changes in nonfarm per capita incomes appeared to be related to size changes on small to midsized farms. Where statistically significant, nonfarm income growth was positively related to the probability of declines in farm sales and negatively related to farm growth. These results may provide some evidence for the short-term role of opportunity costs in encouraging small farm operators to shift from onfarm to off-farm activities.

The proportion of operators working off the farm 200 days or more was positively related to the probabilities of both exit and growth for farms with sales of $40,000-99,999.11/ This result appears to be highly significant in an economic sense as well. This class of midsized farms has been often identified as one under particular stress, due to the combination of high demands on operator labor (making off-farm employment difficult) and farm production volume insufficient to generate adequate income. The data suggest that the combination of this size of farm operation with extensive off-farm work is not sustainable, and operators tend either to leave farming completely or increase their farm size to improve total income.

Because the dependent variable measures change in farm sales in nominal dollars, the rate of change in farm product prices is notable for its lack of statistical significance. This is probably explained by the width of the sales intervals used and the fact that, within each sales class, farms tend to be clustered near the low end. Inflation alone was not sufficient to have an appreciable impact on the probability of changes in sales class, even when measured in nominal terms.

The set of regression results chosen for the model are summarized in table 6. This system of equations forms a complete nonstationary Markov model of farm size in gross sales. For rows 1-3 (entry and farms with initial sales of less than $2,500 and sales of $2,500-4,999) and 10 (initial sales of $500,000 or more), no coefficients for the hypothesized exogenous variables were significant at 0.10 under a t-test, so these rows of the matrix were left constant at the observed 1974-78 probabilities. The other six rows of the transition probability matrix, representing farms with beginning sales of $5,000-499,999, vary with the values of the exogenous variables. Cells of these rows with zero coefficients for the exogenous variables are also nonconstant because they take the value of the mean of their logit. When converted back to estimated proportions, they will yield transition

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11/The estimated relationship between growth (p_{78}) and off-farm work is reported in table 6. The logit function relating the probability of exit (p_{71}) to off-farm work was estimated as follows:
$\ln (p_{71}/p_{77}) = -0.418378 + 7.5249$ OFFWRK, $R^2 = 0.7372$, standard error = 0.1608. Because off-farm work and the percentage of older operators were highly correlated (0.602), including both explanatory variables at once did not improve the overall fit.

probabilities that vary according to the values of the logits of the other cells of the row.

A predicted transition probability matrix is developed by inserting the appropriate values of the exogenous variables into the system of equations shown in table 6. Values of the exogenous variables for the entire United States in 1974-78, which are shown in table 7, generate a set of predicted logits, the log of the ratio (p_{ij}/denominator). The predicted logits are then converted to ratios as in equation (10). These are shown in table 8. Finally, the denominator transition probability for each row is derived as in equation (11), and the remaining cells of the matrix are then computed as in (12). The resulting predicted transition probability matrix is shown in table 8.

The nonstationary model of table 6 predicts a matrix very close to the one calculated directly from 1974-78 U.S. longitudinal data, as shown in table 7. The predicted nonstationary matrix exactly matches the directly computed probabilities in rows 1,2,3, and 10 by assumption. For the variable rows of the matrix (4-9), the predicted probabilities give a very close fit as well, with a maximum divergence of about 0.01.

That the nonstationary Markov model gives a good fit to data within the estimation period is not surprising. A more important test of the performance of the model is how well it performs compared with a stationary model in predicting farm structural change after 1978.

Prediction Performance of the Nonstationary Model, 1978-86

To examine the relative performance of the nonstationary Markov model of farms by gross sales class, U.S. farm structure was projected for 1978-86. These projections were compared with those from a stationary Markov model estimated directly from the 1974-78 longitudinal data with the actual distributions of farms by sales.

Projected versus actual farm size distributions (as reported in the 1978 and 1982 Censuses of Agriculture and the 1986 estimate by USDA's National Agricultural Statistics Service (NASS) [24]) are shown in table 8.12/ Because the stationary Markov model was computed directly from the 1978 census and reproduces that distribution exactly, the stationary projection for 1978 is not shown in the table. Projections are based on the actual distributions of 4 years earlier. Thus, the 1982 projections are the result of multiplying the 1978 census distribution by the transition probability matrix for 1978-82, and the 1986 projections are the result of multiplying the 1982 census distribution by the 1982-86 transition probability matrix. Projection errors are not compounded from one interval to the next.

12/NASS estimates of U.S. farm numbers and their distribution by sales class are derived independently from those of the census through an annual sample survey. While NASS estimates may be revised for preceding years following the release of new census data, current NASS estimates of farm numbers and sizes in 1986 bear no functional relation to census data for 1982.

Table 6--Nonstationary Markov model of farms by sales class, estimated from 1974-78 census longitudinal file

Logit of P_{ij}	Coefficients of: Intercept	Nonfarm	Age	Offwrk	R^2	s_{reg}
Rows 1-3 (initial sales up to $4,999): stationary						
Row 4 (initial sales $5,000-9,999):						
p41	0.27750		3.7545 (2.699)		0.217	0.11874
p42	-1.05646					.25558
p43	-2.84807	0.01515* (.0070)			.400	.07457
p44	(denominator)					
p45	-0.08004					.09993
p46	-1.00549					.24780
p47	-2.05253					.32875
p48	-3.81308					.44111
p49	-5.11144					.60222
p410	-7.02599					1.37248
Row 5 (initial sales $10,000-19,999):						
p51	-0.07475		6.4784* (2.959)		.406	.10339
p52	-1.87721					.44226
p53	-1.58102					.30047
p54	-0.71160					.13992
p55	(denominator)					
p56	-0.12566					.09382
p57	-1.13901					.23550
p58	-3.15380					.44486
p59	-4.63195					.73495
p510	-6.77211					1.05668
Row 6 (initial sales $20,000-39,999):						
p61	-0.40461		9.10865*** (2.402)		.673	.12165
p62	-2.93494					.68498
p63	-2.74564					.55483
p64	-1.90150					.37584
p65	-5.62670	-0.03283** (.0011)			.559	.12128
p66	(denominator)					
p67	2.49638	-0.01786* (0.0093)			.347	.10180
p68	-2.31102					.42079
p69	-4.11860					.78214
p610	-6.21380					1.03671

--Continued

Table 6--Nonstationary Markov model of farms by sales class, estimated from 1974-78 census longitudinal file--Continued

Logit of P_{ij}	Coefficients of: Intercept	Nonfarm	Age	Offwrk	R^2	s_{reg}
Row 7 (initial sales $40,000-99,999):						
p71	-1.07203		13.6669*** (2.122)		.855	.11917
p72	-4.15683					.93919
p73	-4.20161					.88762
p74	-3.49926					.55335
p75	-2.53776					.48130
p76	-9.37480	0.05567** (0.0173)			.596	.19154
p77	(denominator)					
p78	-1.19560			4.35799** (1.439)	.567	.13630
p79	-2.91724					.60357
p710	-5.82839					.89029
Row 8 (initial sales $100,000-199,999):						
p81	-1.14645		15.7946*** (1.668)		.928	.08264
p82	-4.43837					1.04519
p83	-4.50985					.90253
p84	-4.07671					.78185
p85	-3.37990					.45994
p86	-2.46915					.35206
p87	-0.68391					.27014
p88	(denominator)					
p89	-0.73835					.20114
p810	-3.51872					.67454
Row 9 (initial sales $200,000-499,999):						
p91	-0.56714		10.0806*** (2.878)		.637	.11093
p92	-4.90484					.85570
p93	-4.91613					1.00920
p94	-4.31181					.76170
p95	-3.86193					.59878
p96	-3.20709					.31777
p97	-1.87134					.39525
p98	-0.90663					.26269
p99	(denominator)					
p910	-1.26206					.29810
Row 10 (initial sales $500,000 and up):			stationary			

--Continued

Table 6--Nonstationary Markov model of farms by sales class, estimated from 1974-78 census longitudinal file--Continued

1. Dependent variable is the logit of p_{ij}, defined as the log of (p_{ij}/denominator).

2. Parameter estimates derived by OLS regression, weighted by farm numbers in size class i by region.

3. Standard errors of parameter estimates in parenthesis.

4. Number of observations = 9.

5. "Stationary" refers to rows fixed at observed 1974-78 transition probabilities.

6. Explanation of exogenous variables:

   Nonfarm = $\mathbf{Nonfarm}_{.,r,74-78}$ =

   (Nonfarm personal income per capita, region r, 1978 / Nonfarm personal income per capita, region r, 1974)*100. Data source: U.S. Department of Commerce, Bureau of Economic Analysis, state level data tape on income, 1969-83. U.S.-level ratios for post-1978 projections computed from data provided in Survey of Current Business, various issues.

   Age = $\mathbf{Age}_{i,r,74}$ =

   Proportion of operators aged 65 and over, size class i, region r, 1974. Source: 1974 Census of Agriculture. U.S.-level data for post-1978 projections taken from 1982 Census of Agriculture.

   Offwrk = $\mathbf{Offwrk}_{i,r,74}$ =

   Proportion of operators working 200 or more days off-farm, size class i, region r, 1974. Source: 1974 Census of Agriculture. U.S.-level data for post-1978 projections taken from 1982 Census of Agriculture.

   s_{reg} =

   Variance of prediction of the estimated logit function (standard deviation of the regression).

7. OLS significance levels:

   * estimate significant at .10 level
   ** estimate significant at .05 level
   *** estimate significant at .01 level

Table 7--Values of exogenous variables used in projections of nonstationary Markov model

Row and sales class	1974-78 Nonfarm	1974-78 Age	1974-78 Offwrk	1978-82 Nonfarm	1978-82 Age	1978-82 Offwrk	1982-86 Nonfarm	1982-86 Age	1982-86 Offwrk
4 $5,000-9,999		.246			.218			.244	
5 $10,000-19,999		.173			.187			.222	
6 $20,000-39,999		.125			.133			.170	
7 $40,000-99,999		.085	.068		.077	.098		.103	.116
8 $100,000-249,999			.073			.061			.069
9 $250,000-499,999			.075			.066			.077
All farms	144.97			141.68			126.40		

Note: No data for empty cells.
Source: U.S. Department of Commerce, Bureau of Economic Analysis, and 1974, 1978, and 1982 Censuses of Agriculture.

For the stationary model, the transition probability matrix in all periods was the one derived in table 3, assuming a population of 5 million potential entrants in each period. For the nonstationary model, transition probability matrices for each period were derived by inserting the appropriate values of the exogenous variables into the system of equations in table 6. The particular transition probability matrix for the projection period was then computed as in table 8. Five million potential entrants were also assumed in the nonstationary model.

The relative prediction performance of farm structure models can be measured in a number of ways. One measure to compare alternative models is the square root of the sum of squared deviations of projected farms by size class. As an alternative, deviations can be weighted by farm size, so that projection errors for numbers of large farms are counted more heavily than those for small farms [5]. Another measure is the sum of absolute differences between the actual and predicted proportional distributions of farms by size [8]. One other possible measure is the percentage of farms in the projected distribution that were misclassified when compared with the actual distribution. This measure can also be either unweighted or weighted by farm size.

The five prediction measures were applied to the projection results of table 9. Summaries of the performance of the two models are presented in table 10. After the 1974-78 period, for which the stationary model performs perfectly (as expected) and the nonstationary model gives small errors, the nonstationary Markov model demonstrates better predictive power in both future periods according to all five criteria. While the differences between the two models in the accuracy of predicting the 1982 farm size distribution are not dramatic, they are more apparent when the 1986 projections are compared. The nonstationary model appears to have captured, at least partially, some of the effects of the changed farm economic performance of the 1980's.

The superior performance of the nonstationary Markov model in making one-step-ahead farm structure projections suggests that it should also perform better

Table 8--Example of estimated U.S. transition probabilities from nonstationary Markov model, 1974-78

Predicted ratios (p_{ij}/p_{id}), calculated as $e^{\alpha + \beta X + 0.5s^2}$:1/

Row--										
1	Constant									
2	Constant									
3	Constant									
4	3.3461	0.3592	0.5226	1.0000	0.9277	0.3773	0.1355	0.0243	0.0072	0.0023
5	2.8652	.1687	.2153	.4957	1.0000	.8858	.3291	.0471	.0128	.0020
6	2.0988	.0672	.0749	.1603	.4231	1.0000	.9162	.1083	.0221	.0034
7	1.1004	.0243	.0222	.0352	.0887	.2764	1.0000	.4103	.0649	.0044
8	1.0100	.0204	.0165	.0230	.0378	.0901	.5234	1.0000	.4877	.0372
9	1.2129	.0107	.0122	.0179	.0252	.0426	.1664	.4181	1.0000	.2959
10	Constant									

Predicted transition probabilities:

Row--											Row sum:
1	0.7890	0.0557	0.0307	0.0293	0.0262	0.0249	0.0278	0.0097	0.0051	0.0018	1.0000
2	.5726	.1950	.1131	.0710	.0295	.0109	.0056	.0016	.0007	.0001	1.0000
3	.5196	.0965	.1292	.1442	.0732	.0245	.0098	.0020	.0007	.0001	1.0000
4	.4992	.0536	.0780	.1492	.1384	.0563	.0202	.0036	.0011	.0003	1.0000
5	.4758	.0280	.0357	.0823	.1661	.1471	.0547	.0078	.0021	.0003	1.0000
6	.4306	.0138	.0154	.0329	.0868	.2052	.1880	.0222	.0045	.0007	1.0000
7	.3636	.0080	.0073	.0116	.0293	.0913	.3304	.1356	.0214	.0014	1.0000
8	.3111	.0063	.0051	.0071	.0117	.0277	.1612	.3081	.1502	.0115	1.0000
9	.3788	.0033	.0038	.0056	.0079	.0133	.0520	.1306	.3123	.0924	1.0000
10	.5463	.0020	.0011	.0017	.0028	.0054	.0125	.0242	.0898	.3141	1.0000

Transition probabilities calculated directly from 1974-78 longitudinal data:

Row:											Row sum:
1	0.7890	0.0557	0.0307	0.0293	0.0262	0.0249	0.0278	0.0097	0.0051	0.0018	1.0000
2	.5726	.1950	.1131	.0710	.0295	.0109	.0056	.0016	.0007	.0001	1.0000
3	.5196	.0965	.1292	.1442	.0732	.0245	.0098	.0020	.0007	.0001	1.0000
4	.4981	.0537	.0771	.1515	.1396	.0556	.0197	.0034	.0010	.0002	1.0000
5	.4747	.0270	.0349	.0821	.1686	.1496	.0540	.0072	.0018	.0002	1.0000
6	.4306	.0120	.0137	.0309	.0830	.2083	.1969	.0204	.0037	.0005	1.0000
7	.3674	.0061	.0055	.0109	.0262	.0868	.3419	.1357	.0182	.0013	1.0000
8	.3154	.0045	.0037	.0055	.0112	.0271	.1600	.3149	.1484	.0093	1.0000
9	.3828	.0026	.0027	.0044	.0065	.0133	.0486	.1286	.3202	.0903	1.0000
10	.5463	.0020	.0011	.0017	.0028	.0054	.0125	.0242	.0898	.3141	1.0000

Predicted transition probabilities minus those calculated directly:

Row--											Row sum:
1	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0
4	.0011	- .0001	.0008	- .0023	- .0012	.0007	.0006	.0002	.0001	.0002	.0000
5	.0011	.0011	.0008	.0003	- .0025	- .0025	.0007	.0006	.0003	.0001	.0000
6	- .0001	.0018	.0017	.0020	.0038	- .0032	- .0089	.0018	.0009	.0002	.0000
7	- .0039	.0020	.0018	.0007	.0031	.0045	- .0116	- .0001	.0033	.0002	.0000
8	- .0043	.0018	.0013	.0016	.0005	.0007	.0012	- .0068	.0018	.0021	.0000
9	- .0040	.0008	.0011	.0012	.0013	.0000	.0034	.0020	- .0079	.0021	.0000
10	0	0	0	0	0	0	0	0	0	0	0

1/Logits predicted from coefficients and values of exogenous variables reported in table 6.

Table 9--Actual and projected farms by sales class, 1974-86 1/

Sales class	1974 Census	1978 Census	1978 Nstat.	1982 Census	1982 Nstat.	1982 Stat.	1986 NASS	1986 Nstat.	1986 Stat.
					Thousands				
Less than $2,500	649,448	460,535	459,903	536,327	427,854	431,880	580,068	435,355	438,036
$2,500-4,999	257,263	300,699	300,686	278,208	285,696	287,779	307,746	280,027	287,216
$5,000-9,999	296,373	314,088	313,758	281,802	309,892	310,417	265,680	296,854	301,226
$10,000-19,999	310,011	299,215	300,399	259,007	295,566	298,631	236,898	264,584	282,234
$20,000-39,999	321,771	299,175	300,026	248,825	291,131	298,765	223,614	243,200	278,507
$40,000-99,999	324,310	360,093	355,995	332,751	377,432	376,139	294,462	353,196	360,696
$100,000-199,999 2/	101,153	141,050	141,508	180,689	173,130	161,386	305,532	300,531	294,069
$200,000-499,999	40,034	62,645	62,650	93,891	79,105	77,152			
$500,000 and over	11,412	17,973	17,827	27,800	22,597	22,566			
Total farms	2,311,775	2,255,473	2,251,941	2,239,300	2,262,404	2,264,716	2,214,000	2,173,747	2,241,983

Census = Census of Agriculture [25, 26, 27].
Nstat. = Nonsationary Markov model estimated from 1974-78 longitudinal census data.
Stat. = Stationary Markov model estimates from 1974-78 longitudinal census data.
NASS = Estimate of farm numbers and sizes from NASS [24].
1/ Projections are from the census distribution of 4 years earlier. The stationary projection for 1978 is exact because of assumptions used to construct the model.
2/ Figures for $100,000-199,999 in 1986 are for all farms with sales over $100,000. All projections use the known distribution of 4 years earlier as a starting point. Thus, errors are not compounded from one period to the next.

Table 10--Comparison of alternative projection methods, 1978-86 1/

Measures of projection accuracy	1978 Nonstat.	1982 Stat.	1982 Nonstat.	1986 Stat.	1986 Nonstat.
Percentage misclassified	0.38	14.15	13.18	16.98	14.21
Weighted percentage misclassified	0.55	15.81	13.92	11.47	7.98
Square root of sum of squared deviations	4,620	135,817	134,302	177,327	165,248
Square root of sum of squared weighted deviations (x 10^6)	371.7	10,928.2	10,193.0	5,269.3	4,256.0
Sum of absolute proportional differences	0.0039	0.1371	0.1279	0.1687	0.1438

Nstat.= Nonstationary Markov model estimated from 1974-78 longitudinal data.
Stat.= Stationary Markov model estimated from 1974-78 longitudinal data.
1/Projections are from the census distribution of 4 years earlier. Projection accuracy for 1978 and 1982 is measured against distributions published in the 1982 Census of Agriculture [27]. Accuracy for 1986 is measured against the annual estimate provided by NASS [24]. The stationary projection for 1978 is exact because of assumptions used to construct the model.
2/Weighted measures are weighted by the midpoint of the sales classification. The open-ended sales class was weighted by the class average for 1974.

in the more realistic test of projecting several periods ahead. This comparison is made in table 11, which shows projections to 1986 using the 1974 census distribution as a starting point.13/ For the nonstationary model, new values for the exogenous variables were inserted at each iteration. Projection errors are allowed to accumulate from one period to the next. These data are also summarized in figures 3-6.

Projecting ahead three time periods to 1986, the nonstationary Markov model gives results that are closer to the NASS estimates for all gross sales classes above $5,000. For farms with gross sales of $2,500-4,999, NASS estimates an increase of approximately 22,000 farms since 1982, the nonstationary model projects a decline of nearly 4,000 farms, and the stationary model projects little change from 1982. The nonstationary model also projects a steeper decline in the number of smallest farms (under $2,500 sales) than either the stationary model or NASS.

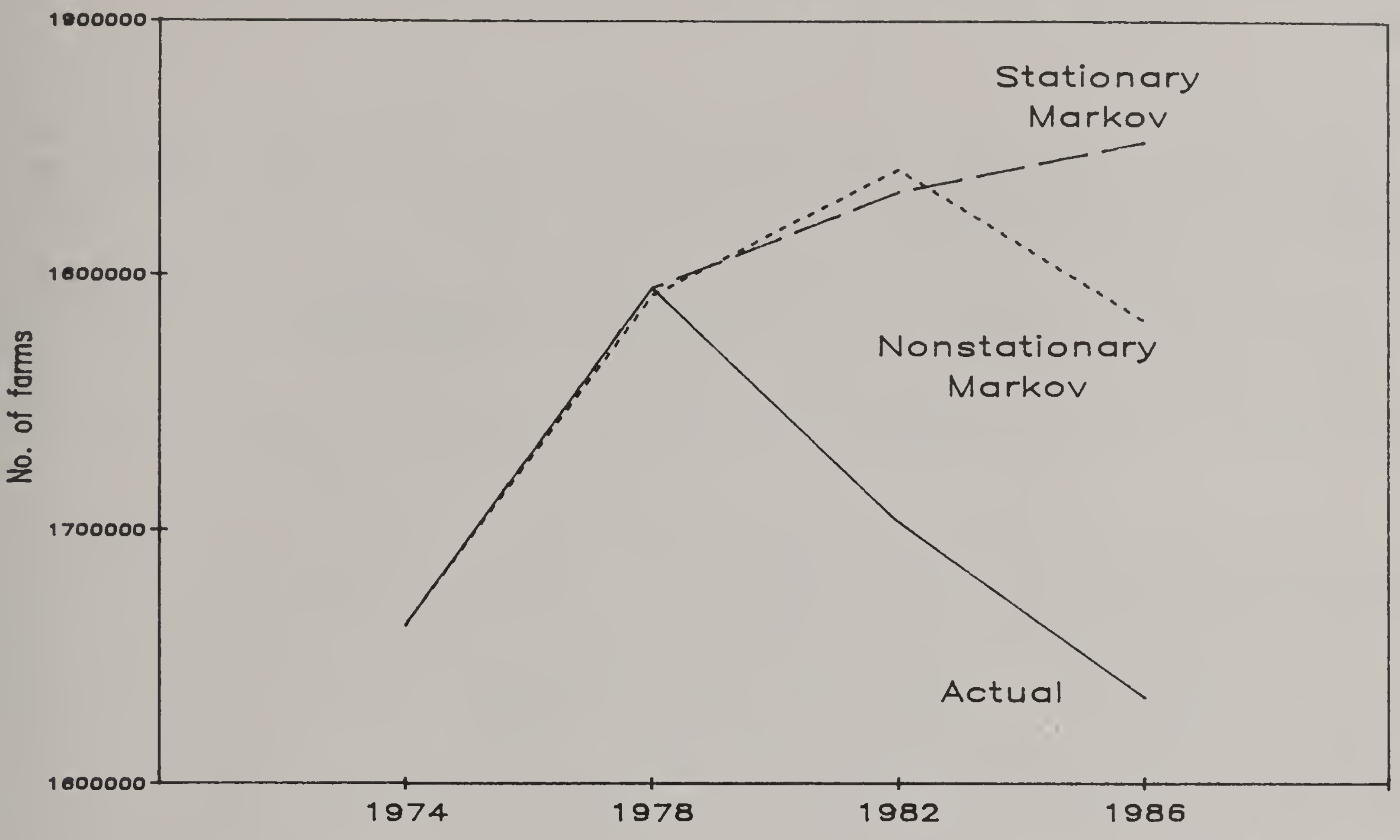
Table 11--Actual and projected farms by sales class, 1974-86. 1/

Sales	1974	1978		1982			1986		
class	Census	Census	Nstat.	Census	Nstat.	Stat.	NASS	Nstat.	Stat.
Less than $2,500	649,448	460,535	459,093	536,327	430,900	431,873	580,068	420,810	424,538
$2,500-4,999	257,263	300,699	300,686	278,208	287,373	287,772	307,746	274,025	282,478
$5,000-9,999	296,373	314,088	313,758	281,802	311,563	310,412	265,680	300,499	305,985
$10,000-19,999	310,011	299,215	300,399	259,007	297,187	298,628	236,898	275,441	296,706
$20,000-39,999	321,771	299,175	300,026	248,825	292,616	298,758	223,614	257,942	299,681
$40,000-99,999	324,310	360,093	355,995	332,751	377,947	376,133	294,462	377,563	384,905
$100,000-199,999 2/	101,153	141,050	141,508	180,689	173,216	161,384	305,532	296,597	282,684
$200,000-499,999	40,034	62,645	62,650	93,891	79,395	77,144			
$500,000 and over	11,412	17,973	17,827	27,800	22,660	22,562			
Total farms	2,311,775	2,255,473	2,251,941	2,239,300	2,272,852	2,264,715	2,214,000	2,202,877	2,276,977

Census = Census of Agriculture [25, 26, 27].
Nstat. = Nonsationary Markov model estimated from 1974-78 longitudinal census data.
Stat. = Stationary Markov model estimates from 1974-78 longitudinal census data.
NASS = Estimate of farm numbers and sizes from NASS [24].
1/Projections are from the census distribution of 4 years earlier. The stationary projection to 1978 is exact due to assumptions used.
2/Figures for $100,000-199,999 in 1986 are for all farms with sales over $100,000. All projections use the known distribution of 4 years earlier as a starting point. Thus, errors are not compounded from one period to the next.

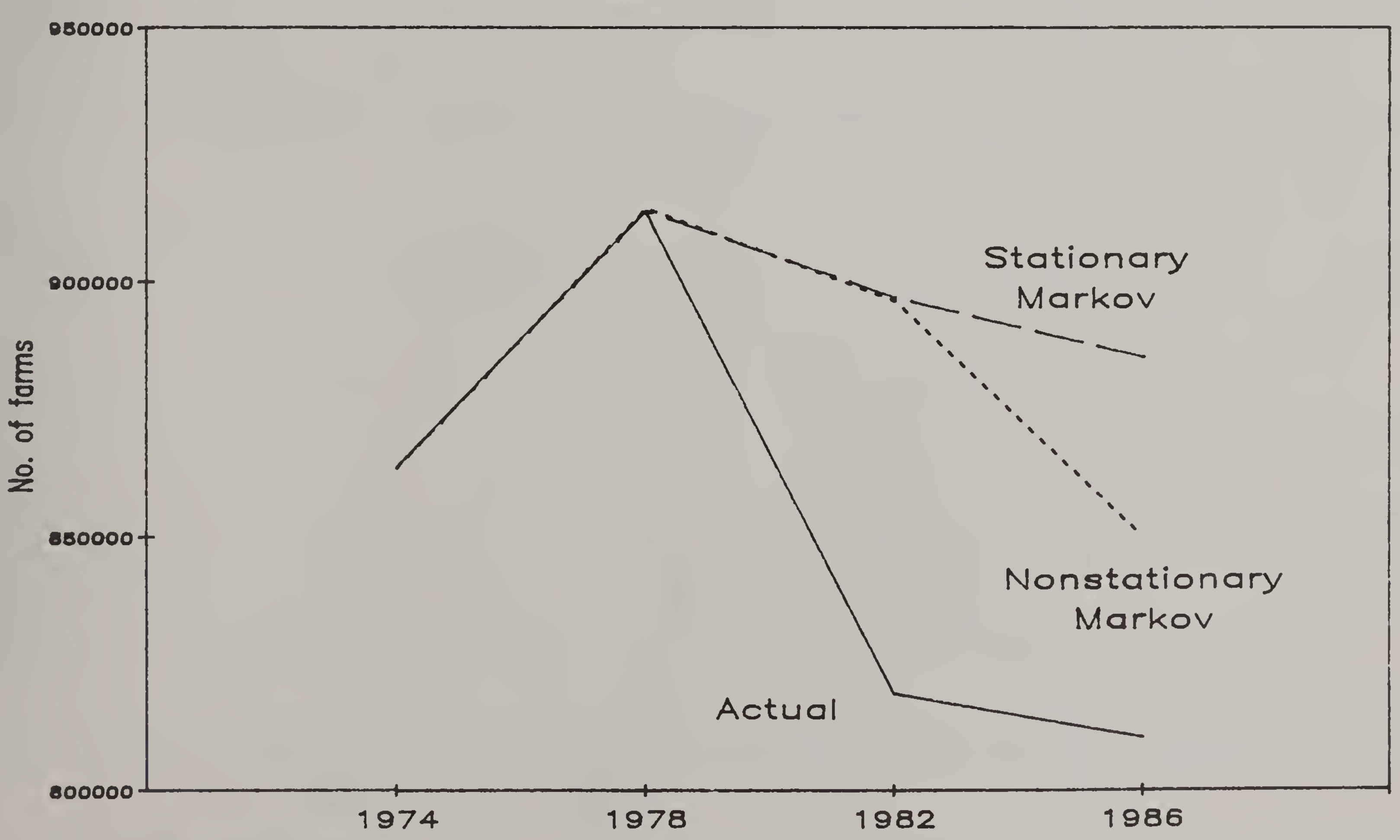
13/Another variant of the stationary model (using each of the nine divisional transition probability matrices held constant at the 1974-78 values, projecting forward from the 1974 divisional size distribution, and then aggregating them after each iteration to form a U.S.-level projection) yielded virtually the same results as the U.S.-level stationary projection computed directly from the U.S. transition matrix. This is to be expected, given that the U.S.-level transition matrix is merely a weighted average of the divisional matrices.

Figure 3. Projected and Actual Farms by Size, 1974-86
All farms with sales of $2,500 and more



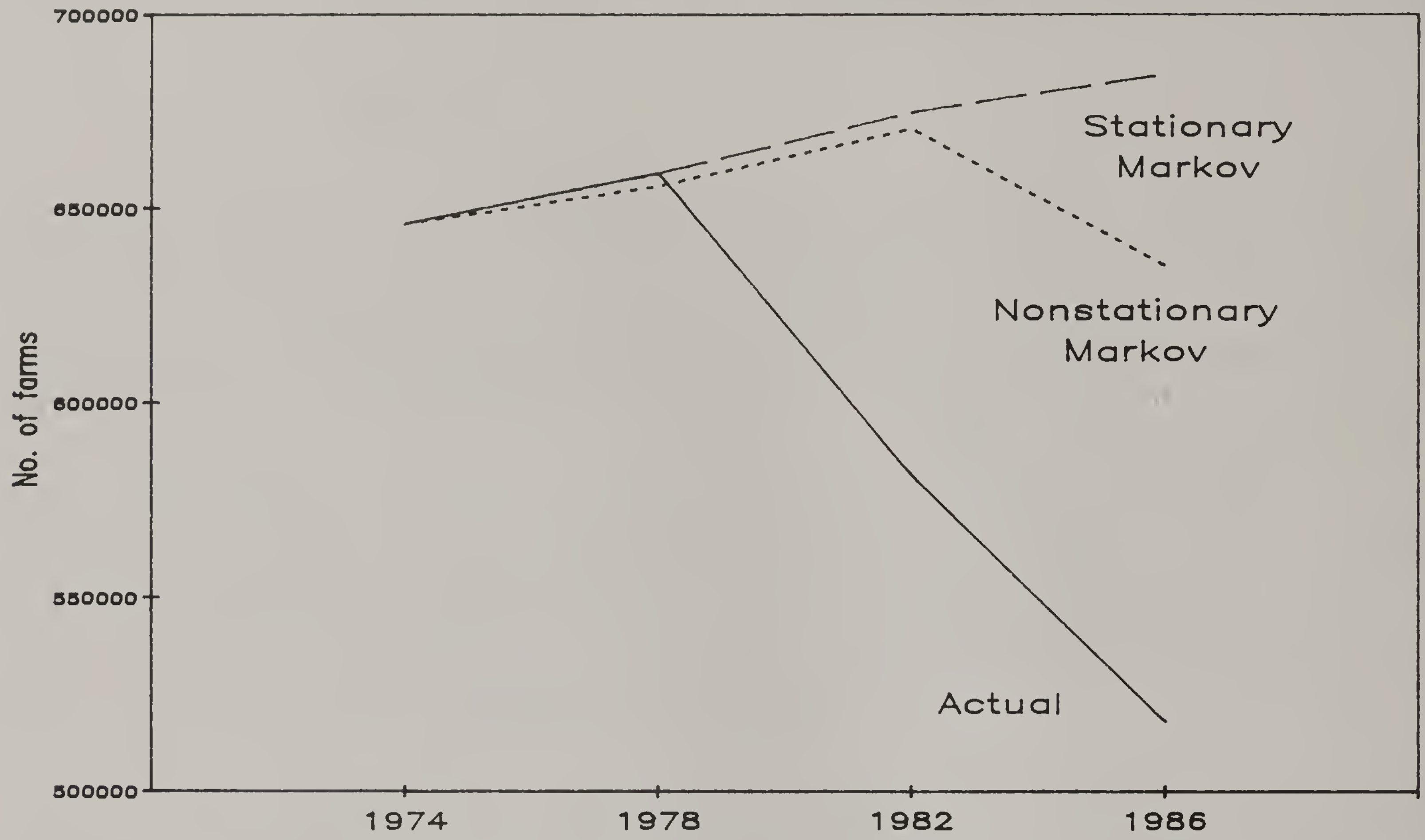
Source: Table 10.

Figure 4. Projected and Actual Farms by Size, 1974-86
Farms with sales of $2,500 to $19,999



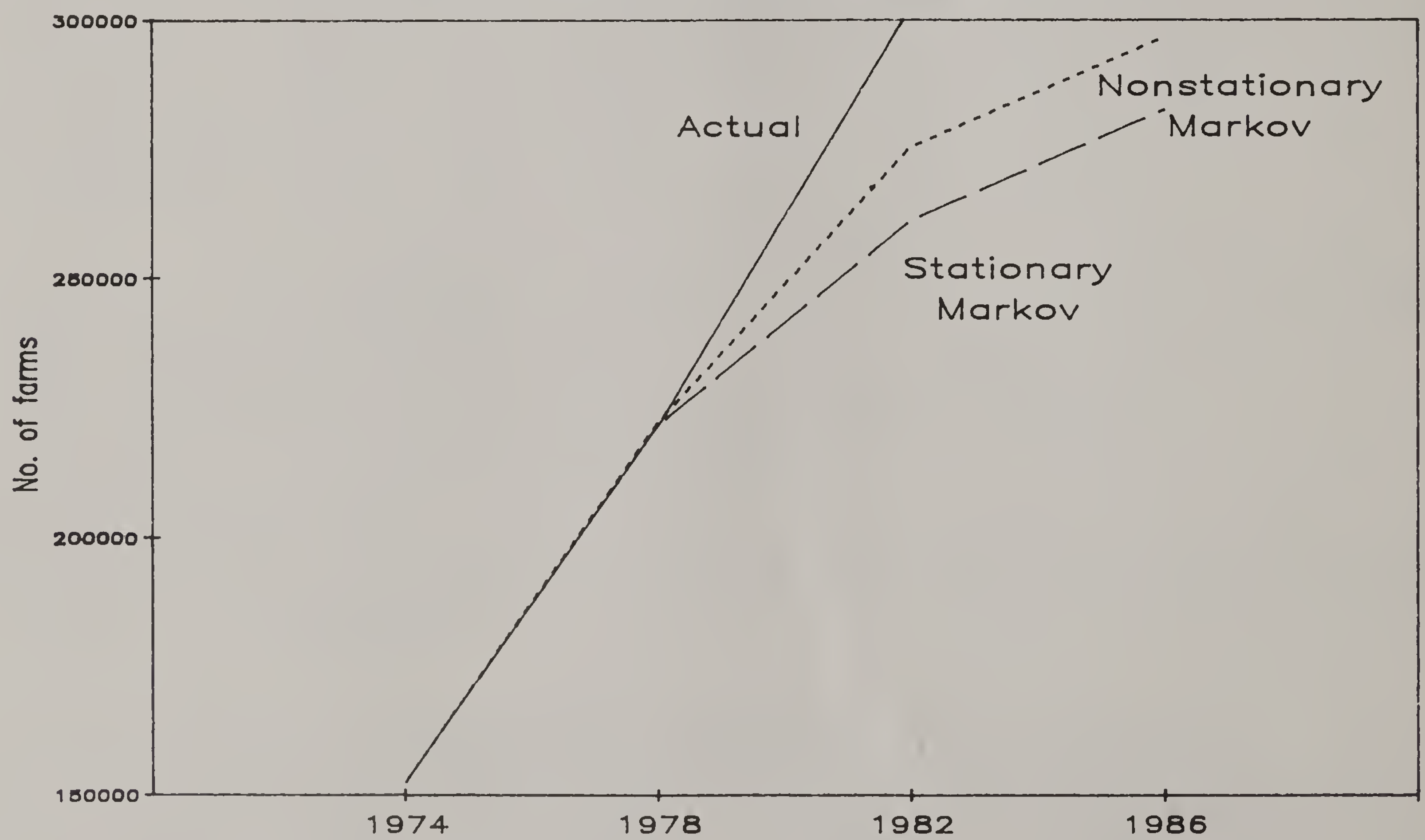
Source: Table 10.

Figure 5. Projected and Actual Farms by Size, 1974-86
Farms with sales of $20,000 to $99,999



Source: Table 10.

Figure 6. Projected and Actual Farms by Size, 1974-86
Farms with sales of $100,000 and more



Source: Table 10.

Obtaining reliable counts of the number of very small farms is difficult for two reasons. First, obtaining a complete census enumeration of very small farms is difficult. Second, the practice of classifying places as farms on the basis of potential and actual farm product sales and the change in methods of evaluating the level of potential sales from one year to the next may cause fluctuations in the numbers of very small farms reported from one period to the next [8, p. 9]. Thus, the official census and NASS estimates of small farm numbers are themselves subject to somewhat greater uncertainty than those for larger farms and form a less rigid standard against which to measure the performance of farm structure models.

The nonstationary model performs particularly well in tracking relative changes in the numbers of small and midsized farms ($20,000-99,999 gross sales) (fig. 5). The actual number of farms in this size class increased over the 1974-78 sample period and then declined. The stationary Markov model continues to project growth in the number of farms in this sales class through 1986. The nonstationary model projects an increase in the number of farms to 1982 but a decline for 1982-86. The nonstationary model was able to capture (albeit lagged one period) an inflection point in farm numbers outside the sample data set.

CONCLUSIONS

This report cites three major reasons for the difficulty of developing conditional projections of U.S. farm structure. These are the lack of an adequate, tractable, theoretical framework through which to aggregate the microlevel responses of hundreds of thousands of individual firms, the lack of data relating microlevel to macrolevel changes in farm structure, and the resulting reliance on analytical methods designed only to identify and extrapolate from historical trends. Two of these obstacles have been largely overcome. Recent successes in linking together the individual respondent records from successive censuses of agriculture have made available for the first time a broad data base on the farm-level components of structural change. This data base is under further development and is intended ultimately to include data from the 1974, 1978, 1982, and future censuses of agriculture. The census longitudinal data offer new possibilities for the analysis and projection of structural change in farming through both refinements of traditional stationary Markov analysis [8] and the development of nonstationary models like the one described here. Methods for incorporating variable transition probabilities while meeting the mathematical restrictions of the Markov model have also been developed, allowing the fullest use of available data on farm size changes [20]. With a larger number of more heterogeneous observations of transition probabilities and exogenous factors covering multiple time periods, more detailed models could be developed that are better suited to the analysis of the structural impacts of alternative policies and economic environments than the model estimated in this paper, which was based on a limited number of somewhat heterogeneous regions over a single 4-year period.

Two of the three major difficulties can thus be surmounted. The third, the inadequacy of our theoretical understanding of the link between firm-level management responses and aggregate sectoral change, remains before us. Which factors are fundamental causes of structural change in agriculture? How are

they transmitted through the decisions of individual farm operators and others? What are the linkages and channels of feedback among farmers' simultaneous managment decisions? Through what channels do public policies influence structural change? A clearer theoretical guide to these relationships would aid in model specification. Teigen [22] explores some of these linkages in a simulation model, where technological diffusion among farms, its impacts on aggregate markets, and resulting feedbacks on per-farm profitability drive structural changes in the farm sector. This would seem to be a fruitful area for further investigation.

Another area of improvement in Markov models of farm structure lies in incorporating demographic effects more directly. Representing rates of entry of new operators as a cohort phenomenon keyed to changes in the number of farm youth able, available, and willing to take up careers in farming would bring the Markov approach to farm structural change into greater harmony with another of the most commonly used quantitative methods in farm structure research, age cohort analysis, as well as eliminate the uncertainties surrounding any arbitrary estimate of a fixed pool of "would-be" farmers.

Conditional projections of farm numbers and sizes hold the potential to contribute significantly in the formation of public policy. Farm structure and structural impacts often figure prominently, even when not cited explicitly, in debates over food, agricultural, and rural development policy. Projections of farm structure are themselves often an important element of these discussions. It is widely shared among economists, policymakers, and the public that, even if only dimly understood, structural change in U.S. agriculture is not an autonomous process. A wide range of factors, some of which can be controlled or influenced by public policy and some of which can not, will determine farm numbers, sizes, and characteristics. Thus, developing models that can reflect, at least in part, the range of alternative futures for the farm sector would seem to be a positive step.

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Appendix table 1--Transition probability matrix, farms by sales 1974-78, census division 1 (New England)

1974 sales	i =	0 (exit) j = 1	Less than $2,500 2	$2,500-4,999 3	$5,000-9,999 4	$10,000-19,999 5	$20,000-39,999 6	$40,000-99,999 7	$100,000-199,999 8	$200,000-499,999 9	$500,000 and over 10	1974 total	1974 number of farms
		1978 sales											
		Probability of transition from state i (1974) to j (1978)											
0 (entry)	1	0.7649	0.0851	0.0332	0.0241	0.0189	0.0213	0.0316	0.0124	0.0061	0.0023	1.0000	50,180
Less than $2,500	2	.5443	.2644	.1012	.0492	.0219	.0107	.0062	.0009	.0010	.0000	1.0000	6,886
$2,500-4,999	3	.5181	.1456	.1415	.1180	.0439	.0174	.0128	.0015	.0005	.0005	1.0000	1,957
$5,000-9,999	4	.4823	.1010	.1054	.1399	.1015	.0453	.0192	.0039	.0015	.0000	1.0000	2,030
$10,000-19,999	5	.4610	.0527	.0493	.0696	.1624	.1506	.0472	.0055	.0013	.0004	1.0000	2,371
$20,000-39,999	6	.4347	.0216	.0187	.0368	.0561	.1973	.2210	.0108	.0023	.0006	1.0000	3,421
$40,000-99,999	7	.3737	.0115	.0059	.0127	.0262	.0554	.3586	.1454	.0099	.0007	1.0000	4,423
$100,000-199,999	8	.3644	.0036	.0029	.0051	.0080	.0202	.0998	.3297	.1605	.0058	1.0000	1,383
$200,000-499,999	9	.3621	.0052	.0034	.0017	.0052	.0121	.0345	.1207	.3483	.1069	1.0000	580
$500,000 and over	10	.6800	.0000	.0000	.0000	.0000	.0000	.0067	.0133	.0467	.2533	1.0000	150

Source: 1974-78 Census of Agriculture longitudinal file and 1974 Census of Agriculture published data. Number of potential entrants in 1974 derived from U.S. total estimate of 5 million, apportioned by share of total U.S. farm numbers by division. For further explanation of methods used to derive transition probabilities, see table 2.

Appendix table 2--Transition probability matrix, farms by sales 1974-78, census division 2 (Mid Atlantic)

1974 sales	i =	0 (exit) j = 1	Less than $2,500 2	$2,500-4,999 3	$5,000-9,999 4	$10,000-19,999 5	$20,000-39,999 6	$40,000-99,999 7	$100,000-199,999 8	$200,000-499,999 9	$500,000 and over 10	1974 total	1974 number of farms
		1978 sales											
		Probability of transition from state i (1974) to j (1978)											
0 (entry)	1	0.7761	0.0711	0.0321	0.0264	0.0211	0.0218	0.0360	0.0099	0.0041	0.0012	1.0000	225,214
Less than $2,500	2	.5662	.2130	.1126	.0682	.0248	.0090	.0051	.0007	.0003	.0001	1.0000	29,905
$2,500-4,999	3	.4758	.1280	.1537	.1476	.0618	.0213	.0101	.0011	.0004	.0001	1.0000	9,771
$5,000-9,999	4	.4515	.0691	.1001	.1733	.1417	.0426	.0188	.0018	.0012	.0000	1.0000	11,136
$10,000-19,999	5	.4302	.0372	.0452	.0868	.1814	.1655	.0477	.0048	.0010	.0002	1.0000	12,517
$20,000-39,999	6	.3991	.0118	.0149	.0305	.0644	.2064	.2587	.0114	.0022	.0006	1.0000	17,091
$40,000-99,999	7	.3641	.0042	.0040	.0084	.0204	.0481	.4020	.1376	.0102	.0008	1.0000	17,883
$100,000-199,999	8	.3418	.0025	.0025	.0045	.0092	.0180	.0922	.3540	.1643	.0110	1.0000	4,011
$200,000-499,999	9	.3617	.0021	.0021	.0041	.0069	.0083	.0304	.0878	.3845	.1120	1.0000	1,446
$500,000 and over	10	.5339	.0000	.0000	.0000	.0054	.0000	.0054	.0136	.1030	.3388	1.0000	369

Source: 1974-78 Census of agriculture longitudinal file and 1974 Census of Agriculture published data. Number of potential entrants in 1974 derived from U.S. total estimate of 5 million, apportioned by share of total U.S. farm numbers by division. For further explanation of methods used to derive transition probabilities, see table 2.

Appendix table 3--Transition probability matrix, farms by sales 1974-78, census division 3 (East North Central)

1974 sales	i =	0 (exit) j = 1	Less than $2,500 2	$2,500-4,999 3	$5,000-9,999 4	$10,000-19,999 5	$20,000-39,999 6	$40,000-99,999 7	$100,000-199,999 8	$200,000-499,999 9	$500,000 and over 10	1974 total	1974 number of farms
		Probability of transition from state i (1974) to j (1978)											
0 (entry)	1	0.8072	0.0418	0.0256	0.0270	0.0262	0.0264	0.0306	0.0101	0.0042	0.0009	1.0000	961,374
Less than $2,500	2	.5948	.1831	.1079	.0676	.0284	.0107	.0059	.0012	.0003	.0000	1.0000	89,608
$2,500-4,999	3	.5402	.0925	.1330	.1395	.0645	.0202	.0082	.0014	.0004	.0000	1.0000	46,016
$5,000-9,999	4	.5015	.0459	.0750	.1613	.1455	.0500	.0176	.0027	.0004	.0001	1.0000	63,024
$10,000-19,999	5	.4614	.0209	.0295	.0766	.1828	.1713	.0509	.0057	.0009	.0001	1.0000	71,975
$20,000-39,999	6	.4078	.0080	.0102	.0256	.0731	.2214	.2338	.0179	.0021	.0002	1.0000	75,493
$40,000-99,999	7	.3413	.0037	.0031	.0073	.0193	.0742	.3803	.1552	.0151	.0005	1.0000	72,343
$100,000-199,999	8	.2955	.0016	.0020	.0029	.0070	.0182	.1581	.3583	.1514	.0049	1.0000	19,799
$200,000-499,999	9	.3851	.0013	.0013	.0031	.0051	.0101	.0439	.1342	.3465	.0694	1.0000	5,446
$500,000 and over	10	.5417	.0013	.0000	.0025	.0013	.0038	.0139	.0215	.0934	.3207	1.0000	792

Source: 1974-78 Census of Agriculture longitudinal file and 1974 Census of Agriculture published data. Number of potential entrants in 1974 derived from U.S. total estimate of 5 million, apportioned by share of total U.S. farm numbers by division. For further explanation of methods used to derive transition probabilities, see table 2.

Appendix table 4--Transition probability matrix, farms by sales 1974-78, census division 4 (West North Central)

1974 sales	i =	0 (exit) j = 1	Less than 2,500 2	$2,500-4,999 3	$5,000-9,999 4	$10,000-19,999 5	$20,000-39,999 6	$40,000-99,999 7	$100,000-199,999 8	$200,000-499,999 9	$500,000 and over 10	1974 total	1974 number of farms
		Probability of transition from state i (1974) to j (1978)											
0 (entry)	1	0.8107	0.0267	0.0200	0.0249	0.0293	0.0340	0.0381	0.0104	0.0046	0.0013	1.0000	1,237,936
Less than $2,500	2	.5719	.1538	.1116	.0878	.0442	.0184	.0094	.0021	.0007	.0001	1.0000	80,428
$2,500-4,999	3	.5384	.0752	.1090	.1408	.0867	.0334	.0136	.0022	.0006	.0001	1.0000	46,772
$5,000-9,999	4	.5128	.0387	.0680	.1408	.1457	.0660	.0236	.0036	.0007	.0002	1.0000	68,625
$10,000-19,999	5	.4813	.0177	.0279	.0788	.1706	.1570	.0589	.0064	.0013	.0001	1.0000	93,832
$20,000-39,999	6	.4237	.0072	.0099	.0267	.0896	.2266	.1951	.0185	.0024	.0003	1.0000	118,933
$40,000-99,999	7	.3349	.0031	.0034	.0082	.0259	.1046	.3738	.1309	.0146	.0007	1.0000	120,514
$100,000-199,999	8	.2626	.0019	.0019	.0037	.0091	.0289	.2037	.3434	.1371	.0076	1.0000	31,554
$200,000-499,999	9	.3516	.0013	.0008	.0022	.0051	.0107	.0570	.1553	.3335	.0824	1.0000	9,816
$500,000 and over	10	.5766	.0016	.0016	.0021	.0011	.0090	.0185	.0296	.0957	.2643	1.0000	1,892

Source: 1974-78 Census of Agriculture longitudinal file and 1974 Census of Agriculture published data. Number of potential entrants in 1974 derived from U.S. total estimate of 5 million, apportioned by share of total U.S. farm numbers by division. For further explanation of methods used to derive transition probabilities, see table 2.

Appendix table 5--Transition probability matrix, farms by sales 1974-78, census division 5 (South Atlantic)

1974 sales	i =	0 (exit) j = 1	Less than $2,500 2	$2,500-4,999 3	$5,000-9,999 4	$10,000-19,999 5	$20,000-39,999 6	$40,000-99,999 7	$100,000-199,999 8	$200,000-499,999 9	$500,000 and over 10	1974 total	1974 number of farms
		1978 sales											
		Probability of transition from state i (1974) to j (1978)											
0 (entry)	1	0.7742	0.0735	0.0355	0.0312	0.0257	0.0208	0.0222	0.0095	0.0055	0.0019	1.0000	639,889
Less than $2,500	2	.5932	.2156	.1004	.0535	.0218	.0085	.0043	.0015	.0010	.0002	1.0000	110,117
$2,500-4,999	3	.5437	.1110	.1306	.1278	.0582	.0171	.0086	.0020	.0009	.0002	1.0000	36,869
$5,000-9,999	4	.5344	.0682	.0785	.1422	.1141	.0422	.0148	.0038	.0015	.0002	1.0000	39,761
$10,000-19,999	5	.5286	.0380	.0431	.0841	.1494	.1073	.0386	.0078	.0027	.0005	1.0000	35,213
$20,000-39,999	6	.5020	.0198	.0211	.0377	.0776	.1712	.1433	.0209	.0054	.0010	1.0000	28,237
$40,000-99,999	7	.4453	.0116	.0099	.0162	.0288	.0665	.2605	.1338	.0253	.0020	1.0000	27,938
$100,000-199,999	8	.3444	.0091	.0063	.0082	.0138	.0280	.1090	.2932	.1752	.0129	1.0000	11,252
$200,000-499,999	9	.3707	.0056	.0042	.0064	.0088	.0140	.0365	.1022	.3509	.1006	1.0000	4,990
$500,000 and over	10	.5078	.0027	.0041	.0007	.0027	.0034	.0088	.0183	.0805	.3712	1.0000	1,479

Source: 1974-78 Census of Agriculture longitudinal file and 1974 Census of Agriculture published data. Number of potential entrants in 1974 derived from U.S. total estimate of 5 million, apportioned by share of total U.S. farm numbers by division. For further explanation of methods used to derive transition probabilities, see table 2.

Appendix table 6--Transition probability matrix, farms by sales 1974-78, census division 6 (East South Central)

1974 sales	i =	0 (exit) j = 1	Less than $2,500 2	$2,500-4,999 3	$5,000-9,999 4	$10,000-19,999 5	$20,000-39,999 6	$40,000-99,999 7	$100,000-199,999 8	$200,000-499,999 9	$500,000 and over 10	1974 total	1974 number of farms
		1978 sales											
		Probability of transition from state i (1974) to j (1978)											
0 (entry)	1	0.7839	0.0748	0.0421	0.0359	0.0246	0.0163	0.0134	0.0055	0.0028	0.0006	1.0000	661,544
Less than $2,500	2	.6122	.1809	.1075	.0641	.0239	.0072	.0028	.0011	.0004	.0001	1.0000	138,232
$2,500-4,999	3	.5176	.0984	.1416	.1499	.0660	.0192	.0056	.0014	.0003	.0001	1.0000	49,369
$5,000-9,999	4	.4809	.0580	.0853	.1697	.1421	.0484	.0129	.0019	.0007	.0001	1.0000	43,643
$10,000-19,999	5	.4655	.0328	.0429	.0927	.1760	.1396	.0425	.0063	.0016	.0002	1.0000	30,529
$20,000-39,999	6	.4591	.0190	.0223	.0427	.0871	.1831	.1592	.0221	.0049	.0005	1.0000	19,306
$40,000-99,999	7	.4408	.0133	.0121	.0182	.0315	.0695	.2607	.1270	.0252	.0016	1.0000	16,515
$100,000-199,999	8	.3971	.0073	.0060	.0087	.0158	.0268	.1001	.2599	.1677	.0106	1.0000	5,636
$200,000-499,999	9	.4119	.0046	.0050	.0064	.0046	.0159	.0310	.0947	.3359	.0901	1.0000	2,197
$500,000 and over	10	.5351	.0000	.0000	.0000	.0068	.0091	.0091	.0295	.0703	.3401	1.0000	441

Source: 1974-78 Census of Agriculture longitudinal file and 1974 Census of Agriculture published data. Number of potential entrants in 1974 derived from U.S. total estimate of 5 million, apportioned by share of total U.S. farm numbers by division. For further explanation of methods used to derive transition probabilities, see table 2.

Appendix table 7--Transition probability matrix, farms by sales 1974-78, census division 7 (West South Central)

1974 sales	i =	0 (exit) j = 1	Less than $2,500 2	$2,500-4,999 3	$5,000-9,999 4	$10,000-19,999 5	$20,000-39,999 6	$40,000-99,999 7	$100,000-199,999 8	$200,000-499,999 9	$500,000 and over 10	1974 total	1974 number of farms
		Probability of transition from state i (1974) to j (1978)											
0 (entry)	1	0.7735	0.0727	0.0401	0.0336	0.0247	0.0198	0.0206	0.0085	0.0050	0.0016	1.0000	708,916
Less than $2,500	2	.5268	.1978	.1346	.0873	.0338	.0111	.0057	.0020	.0008	.0001	1.0000	132,468
$2,500-4,999	3	.4768	.0907	.1310	.1675	.0902	.0284	.0113	.0028	.0010	.0002	1.0000	43,675
$5,000-9,999	4	.4742	.0553	.0771	.1506	.1478	.0641	.0243	.0052	.0013	.0002	1.0000	40,640
$10,000-19,999	5	.4634	.0321	.0404	.0881	.1564	.1396	.0649	.0114	.0031	.0006	1.0000	33,821
$20,000-39,999	6	.4498	.0203	.0196	.0398	.0897	.1741	.1660	.0322	.0075	.0009	1.0000	28,157
$40,000-99,999	7	.4199	.0115	.0114	.0185	.0327	.0812	.2621	.1328	.0275	.0024	1.0000	29,416
$100,000-199,999	8	.3431	.0089	.0072	.0093	.0180	.0320	.1421	.2763	.1519	.0112	1.0000	12,141
$200,000-499,999	9	.3892	.0024	.0052	.0064	.0099	.0202	.0605	.1363	.2977	.0723	1.0000	5,936
$500,000 and over	10	.5175	.0033	.0013	.0053	.0026	.0079	.0224	.0428	.1187	.2782	1.0000	1,517

Source: 1974-78 Census of Agriculture longitudinal file and 1974 Census of Agriculture published data. Number of potential entrants in 1974 derived from U.S. total estimate of 5 million, apportioned by share of total U.S. farm numbers by division. For further explanation of methods used to derive transition probabilities, see table 2.

Appendix table 8--Transition probability matrix, farms by sales 1974-78, census division 8 (Mountain)

1974 sales	i	0 (exit) = j = 1	Less than $2,500 2	$2,500-4,999 3	$5,000-9,999 4	$10,000-19,999 5	$20,000-39,999 6	$40,000-99,999 7	$100,000-199,999 8	$200,000-499,999 9	$500,000 and over 10	1974 total	1974 number of farms
		Probability of transition from state i (1974) to j (1978)											
0 (entry)	1	0.7598	0.0580	0.0300	0.0298	0.0301	0.0307	0.0342	0.0143	0.0087	0.0044	1.0000	240,458
Less than $2,500	2	.5343	.2181	.1093	.0730	.0349	.0160	.0108	.0025	.0008	.0002	1.0000	23,170
$2,500-4,999	3	.5328	.0982	.1088	.1233	.0808	.0351	.0153	.0042	.0014	.0002	1.0000	10,549
$5,000-9,999	4	.5077	.0540	.0733	.1293	.1307	.0692	.0279	.0050	.0021	.0007	1.0000	13,530
$10,000-19,999	5	.4927	.0273	.0360	.0803	.1452	.1387	.0667	.0104	.0025	.0002	1.0000	15,887
$20,000-39,999	6	.4529	.0139	.0162	.0349	.0907	.1862	.1718	.0262	.0064	.0008	1.0000	17,320
$40,000-99,999	7	.4097	.0056	.0060	.0131	.0347	.1140	.2878	.1051	.0211	.0029	1.0000	19,061
$100,000-199,999	8	.3667	.0051	.0040	.0063	.0122	.0381	.1959	.2456	.1147	.0114	1.0000	6,825
$200,000-499,999	9	.4165	.0038	.0023	.0072	.0075	.0171	.0616	.1409	.2511	.0920	1.0000	3,457
$500,000 and over	10	.5871	.0015	.0000	.0015	.0015	.0058	.0116	.0247	.0929	.2736	1.0000	1,378

Source: 1974-78 Census of Agriculture longitudinal file and 1974 Census of Agriculture published data. Number of potential entrants in 1974 derived from U.S. total estimate of 5 million, apportioned by share of total U.S. farm numbers by division. For further explanation of methods used to derive transition probabilities, see table 2.

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